A WATERSHED-LEVEL ECOLOGICAL RISK ASSESSMENT METHODOLOGY

By

WILLIAM CULLITON HESSION

Bachelor of Science
Virginia Polytechnic Institute and State University
Blacksburg, Virginia
1984

Master of Science
Virginia Polytechnic Institute and State University
Blacksburg, Virginia
1988

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ASSESSMENT METHODOLOGY

Thesis Approved:

Thesis Adviser

Dean of Graduate College

Dedicated to

And

In Memory of

William Joseph Hession, Jr.
(June 15, 1930 - September 19, 1993)

My Father

My Friend

My Hero

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"What would life be if we had no courage to attempt anything?" Vincent Van Gogh

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PREFACE

The research reported herein is presented as a collection of three journal articles. An introduction and thorough literature review (Chapter 1) precedes the articles and contains a separate reference section. Each journal article (Chapters 2, 3, and 4) has its own abstract, introduction, literature review, methodologies, results, conclusions, and reference section. Each article adheres to the style requirements of the journals to which it has been submitted. Detailed information left out of the journal articles is presented in the Appendices for each article separately. Finally, recommendations for future research are presented. The three articles, by chapter, are:

Chapter 2: ***Title:*** Risk Analysis of Total Maximum Daily Loads in an Uncertain Environment Using EUTROMOD. ***Authors:*** W.C. Hession, D.E. Storm, C.T. Haan, K.H. Reckhow, and M.D. Smolen. ***Journal:*** *Lake and Reservoir Management.*

Chapter 3: ***Title:*** Uncertainty and the USLE. ***Authors:*** W.C. Hession, D.E. Storm, and C.T. Haan. ***Journal:*** *Transactions of the ASAE.*

Chapter 4: ***Title:*** A Watershed-Level Ecological Risk Assessment Methodology. ***Authors:*** W.C. Hession, D.E. Storm, C.T. Haan, S.L. Burks, and M.D. Matlock. ***Journal:*** *Journal of Soil and Water Conservation.*

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CHAPTER 1

INTRODUCTION AND LITERATURE REVIEW

INTRODUCTION

Wister Lake, located in southeast Oklahoma, is the sole water supply for the majority of residents in LeFlore and three adjacent counties. In addition, the lake and related recreational activities are important to the economy of the area. The lake receives pollutants from a wide variety of both point and nonpoint sources. Wister Lake has been classified eutrophic since it was surveyed by the U.S. Environmental Protection Agency (U.S. EPA) in 1974 (U.S. EPA, 1977). Oklahoma's 1990 Water Quality Assessment Report for Section 305(b) of the Clean Water Act (CWA) identifies Wister Lake as eutrophic and highly turbid. In addition, Wister Lake's watershed has been targeted in Oklahoma's Section 319 Nonpoint Source (NPS) Management Plan as well as in its Section 303(d) list of total maximum daily load (TMDL) waters.

The State of Oklahoma, using the CWA of 1987 as guidance, has an ongoing cooperative project to improve and prevent further deterioration of water quality in Wister Lake. The ultimate objective of the CWA is "to restore and maintain the chemical, physical, and biological integrity of the Nation's waters." Tansley (1935) defined ecosystem as "a system resulting from the integration of all living and nonliving factors of the environment." Therefore, an ecosystem-based approach, including the integration of chemical, physical, and biological components, is the most logical approach to address CWA goals.

Suter (1993) defined ecological risk assessment as the process of assigning magnitudes and probabilities to the adverse effects of human activities or natural catastrophes. Ecological risk assessments provide a holistic method for analyzing and predicting ecosystem responses to stress. Resource planning and decision making using ecosystem response can be difficult due to lack of knowledge, intricacies of ecosystem function, and minimal data availability. Therefore, simulation models are often used for analyzing and predicting the response of ecosystems to perturbation (Minns, 1992). Uncertainty analyses should be a routine part of ecological risk assessment (Risk Assessment Forum, 1992). However, few, if any, existing pollutant transport and fate models proposed for use in ecological risk assessments include thorough uncertainty analyses (Reckhow, 1994).

There is a growing consensus that the water quality problems now facing society can best be solved by following a basin-wide or watershed protection approach (U.S. EPA, 1991; Doppelt et al., 1993). The CWA, Section 319, requires that States implement NPS management programs to the maximum extent practicable on a watershed-by-watershed basis. In addition, the present reauthorization of the CWA is expected to incorporate a watershed management approach and may include amendments that provide incentives to state and local governments to adopt watershed management plans (Browner, 1993; Perciasepe, 1994). Methodologies and tools for performing ecological risk assessments at the watershed level which are simple, "user friendly," and incorporate thorough uncertainty analyses to allow for appropriate management decisions at the local, state, and federal levels are needed.

THE PROBLEM

Rationale

Ecological risk assessment and watershed-level management are quickly becoming fundamental components of environmental decision making concerning the Nation's water bodies. Geographic information systems (GISs) and simulation models are important tools in water quality management. Uncertainty analyses should be an integral part of ecological risk assessments, but are rarely incorporated thoroughly in pollutant transport and fate models. Appropriate tools and methodologies are needed to allow for ecological risk assessment and watershed management while addressing uncertainties in knowledge, data, and ultimately, predictions. The tools and methodologies should be useful for assessment and decision making at local, state, and federal agencies. Therefore, they must be user friendly and simple, while providing reliable information with quantifiable uncertainty.

Theoretical Framework for Proposed Study

The proposed work is based on the theory that an ecosystem-based approach, where the ecosystem is defined at the watershed level, is the most logical approach to addressing the goals of the CWA as presented in the 1987 NPS amendments. The ecological risk assessment methodology will build on the paradigms and theories laid out by Suter (1993). Reckhow's (1994) suggestion that *all* scientific uncertainties must be estimated and included in ecological risk assessment or modeling activities will be adhered to as much as possible. Finally, methodologies used to incorporate uncertainty into the risk assessment and model will follow fundamentals put forth by Suter et al. (1987), Helton (1994), and MacIntosh et al. (1994). Validation will be performed by comparing model results with in-lake monitoring data from an ongoing U.S. EPA Clean Lakes Project and watershed loading estimates from monitoring stations located on the main tributaries to the lake.

Statement of the Problem

The purpose of this research is to develop an ecological risk assessment methodology at the watershed level for freshwater ecosystems. The main product will be a pollutant transport and fate model (a modified EUTROMOD) with uncertainty analysis integrated as fully as possible considering existing knowledge, data, and technology. The model will allow for ecological risk assessment of lentic ecosystems due to the stress of excess phosphorus. The methodology and model will be tested on the Wister Lake watershed with the lake and its trophic state as the endpoint for ecological risk assessment. Alternative management scenarios will be simulated and recommendations for achieving water quality goals in Wister Lake will be made.

Elements of the Problem (Objectives)

1. Define a methodology for conducting watershed-level ecological risk assessments.
2. Modify EUTROMOD for use in ecological risk assessment.
3. Define methodology for propagating uncertainty throughout risk assessment.
4. Using the proposed methodology and EUTROMOD, evaluate the risk of eutrophication in Wister Lake, Oklahoma as a probabilistic description of uncertain phosphorus inputs.
5. Evaluate alternative management scenarios in the Wister Lake watershed and make recommendations on land use changes and/or management alternatives for achieving water quality objectives in Wister Lake.

PROJECT AREA DESCRIPTION

The Lake and its Watershed

Wister Lake, located in the Arkansas River Basin on the Poteau River, was created by the U.S. Army Corps of Engineers in 1949 to provide flood control, water supply, low flow augmentation, and water conservation. Wister Lake has a surface area of 2,970 ha, a shoreline length of 185 km, a mean depth of 2.3 m, and a maximum depth of 13.4 m at normal pool elevation of 146 m. Wister Lake's watershed covers approximately 260,000 ha with two thirds in Oklahoma and the remainder in Arkansas.

The watershed drains portions of LeFlore and Latimer Counties in Oklahoma, and Scott and Polk Counties in Arkansas.

The lake receives inputs from a wide variety of pollutant sources, both point and nonpoint. There are nine major permitted wastewater treatment plants in Wister Lake's watershed. Nonpoint pollution contributing to the lake includes agricultural, forestry, resource exploration and extraction, and urban sources. A major source of nutrients in the watershed originates from the large poultry rearing and processing industry present in the region. In fact, LeFlore County is one of the largest and most rapidly growing poultry producing counties in Oklahoma. Poultry litter, spread as fertilizer on pastures, may result in a large pollutant source if poorly managed.

The Wister Lake watershed includes portions of the Ouachita Mountains and the Arkansas Valley ecoregions (Omernik, 1987). The Ouachita Mountain ecoregion is described as open high hills to open low mountains, land use of oak/hickory/pine woodland and forest, and soils of moist ultisols. The Arkansas Valley ecoregion is described as plains with hills, land use a mix of cropland with pasture and varied forest types of oak/hickory/pine or oak/tupelo/bald cypress, and soils consisting of altisols and sandstone/shale. Land use in the watershed is approximately three fourths forest and one fourth pasture, with small amounts of cropland, urban, and disturbed land. The topography ranges from level flood plains along Fourche Maline Creek and the Poteau River to gently sloping uplands to steep mountainous areas. The relief ranges from Wister Lake's normal pool elevation to the 817 m peak of Rich Mountain in Arkansas.

Water Quality Monitoring

Presently, a cooperative project is underway to prevent further deterioration of water quality in Wister Lake through control of point and nonpoint pollution sources. Monitoring stations have been established throughout the Wister Lake watershed to assist in determining the magnitude of pollutant loading to the lake, distinguishing sources, and tracking the effectiveness of pollution control activities (Hession et al., 1992; Storm et al., 1994). The U.S. Geological Survey (USGS) and the Oklahoma Conservation Commission (OCC) have established seven water quality/quantity monitoring stations which are sampled at 6-week intervals for flow, nutrients, sediments, and other constituents of concern. In addition, four of these stations have continuous automatic samplers for stream flow monitoring. Figure 1.1 shows the four water quality monitoring stations that define the main subwatersheds addressed throughout this study.

Additional, monitoring activities have also been conducted by the Arkansas Department of Pollution Control and Ecology (ADPC&E) on the Poteau River as well as by consultants hired by the Town of Waldron and Tyson Foods in Arkansas (Storm et al., 1994). In addition, in-lake nutrient and chlorophyll *a* concentrations have been monitored by the Oklahoma Water Resources Board (OWRB) at five different locations within the lake for an ongoing U.S. EPA Clean Lakes Project.

Watershed-Level Data

The Geographic Resources Analysis Support System (GRASS) (U.S. Army,

1991) GIS software on Sun Workstations was utilized to store, manage, and manipulate spatially referenced data for characterizing the Wister Lake watershed. Land use data for the Oklahoma portion of the basin were obtained from the U.S. Natural Resource Conservation Service (NRCS) at a resolution of 4 ha. These data represent land use from between 1982 and 1985. Land use information for the Arkansas portion of the watershed was obtained from the USGS GIRAS (Mitchell et al., 1977) land use and land cover digital database at a resolution of 4 ha. The two land use coverages were categorized using the USGS classification system (Anderson et al., 1976) and merged to create one coverage. This data layer resulted in seven general land use types distributed throughout the basin: cropland, pasture, forest, water, wetlands, urban/built-up, and disturbed land. Disturbed land includes strip mines, gravel pits, and quarries as well as oil and gas exploration disturbances. The Geography Department at Oklahoma State University is presently classifying Landsat Thematic Mapper imagery to provide more detailed, consistent land use data for the entire basin. Unfortunately, the data were unavailable for this project.

Detailed soils data for the Oklahoma portion of the watershed were obtained in digital format from the NRCS at a resolution of 4 ha. These data were developed between 1982 and 1985. The soil surveys for Scott and Polk Counties in Arkansas were not yet available. Instead, the general county-level soil maps for the Arkansas portion of the basin were obtained and digitized into the GIS. A detailed soils data layer is presently being digitized from soil surveys and being combined with existing soil survey data layers from the U.S. Forest Service. These data were unavailable for this project.

The digital elevation maps (DEMs) covering the Wister Lake watershed were purchased from USGS. These data are on a 30 m by 30 m square grid for 7.5' quadrangle coverage, which corresponds to the 1:24,000-scale topographic map series. These DEMs were imported into the GIS and merged to form one elevation file for the entire Wister Lake watershed. This elevation data layer was then used to create a percent slope data coverage for the watershed.

LITERATURE REVIEW

Ecological Risk Assessment

The Paradigm

As a comparatively recent discipline, ecological risk assessment methodologies and concepts are subject to debate and change (Lipton et al., 1993). In addition, risk assessment methodologies dealing with ecosystem responses are difficult to standardize due to the wide variability in the types of ecosystems, intended scopes, available resources, and endpoint objectives. Suter (1993) defined ecological risk assessment as the process of assigning magnitudes and probabilities to the adverse effects of human activities or natural catastrophes. Ecological risk assessments provide a holistic method for analyzing and predicting ecosystem responses to stress. The stressors can be any chemical, physical, or biologic entity that can cause adverse effects on individuals, populations, communities, or ecosystems (U.S. EPA, 1992).

I used the effects-driven retrospective ecological risk assessment paradigm with ecosystem-level effects as described by Suter (1993) for this project. This type of assessment is appropriate where there are observed effects, unknown exposure, and unknown sources. Wister Lake and its tributaries have been identified as having water quality problems and, although there are strong suspects for sources of phosphorus, the amount of exposure and importance and distribution of the sources is unknown. There are four sequential components to this ecological risk assessment: hazard definition, hazard measurement and estimation, risk characterization, and risk management (Suter, 1993). Suter (1990) also points out that an ecological risk assessment begins with three activities: choosing endpoints, describing the environment, and describing the hazard. Lipton et al. (1993) proposed a paradigm for ecological risk assessment composed of seven steps: receptor identification, hazard identification, endpoint identification, relationship assessment, exposure assessment, response assessment, and risk characterization/uncertainty analysis.

Resource planning and decision making using ecosystem response can be difficult due to lack of knowledge, intricacies of ecosystem function, and minimal data availability. Often, the determining factor in the accuracy of an ecological risk assessment is the availability of long-term, multivariate field data (Cairns and Neiderlehner, 1993). However, simulation models are often used as an alternative to field observations for analyzing and predicting the response of ecosystems to perturbation (Minns, 1992). Uncertainty analyses should be a routine part of ecological risk assessments (Risk Assessment Forum, 1992; Lipton et al., 1993; Reckhow, 1994). The result of an ecological risk assessment should be a probabilistic estimate of the ecological effects resulting from specific levels of stress (Cairns and Pratt, 1990; Cairns and McCormick, 1991).

The Ecosystem

There are many references that suggest and justify watersheds as the preferred ecosystem when dealing with water quality concerns. Reynolds (1993), in discussing the ecosystems approach to water management, stressed that rivers and lakes belong to ecosystems which encompass their entire drainage basins. Stanford and War (1992) defined watershed as the ridgeline or elevation contour that delimits drainage basins or catchments where the catchment is bounded by the watershed, and can be defined as a land area drained by a river/stream or system of connecting rivers/streams such that all water within the area flows through a single outlet. Doppelt et al. (1993) described watersheds as "ecosystems composed of a mosaic of different land or terrestrial patches that are connected by (drained by) a network of streams." They further described watersheds as involving four-dimensional processes that connect longitudinal, lateral, and vertical dimensions, each differing temporally.

Odum (1969) stated that the entire drainage or catchment basin, not just the lake or stream, must be considered the ecosystem unit in order to deal successfully with water pollution problems. He considered streams embedded in the watershed to be the integrated result of ecosystem processes. Hynes (1975) encouraged a holistic view of watercourses, suggesting that streams not be viewed as purely aquatic phenomena, but rather as parts of the valleys that they drain. Stanford and Ward (1992) reasoned that, since water flows downstream from the watershed through the catchment, thereby integrating influences of natural and human disturbances within the catchment, the watershed is a natural ecosystem boundary. Lotspeich (1980), while noting that streams are the integrated product of their watershed, defined watersheds as the basic ecosystem.

The Stressor

The pollutants of concern in Wister Lake and its tributaries are nutrients (phosphorus and nitrogen) and sediment (Hession et al., 1992; Storm et al, 1994). The work performed herein specifically addresses phosphorus and its effect on the aquatic environment (Wister Lake).

The trophic state of a water body refers to its productivity level which can be affected by, but not defined by, its nutrient status. Lakes are often classified as oligotrophic, mesotrophic, or eutrophic based on their primary productivity and other attributes. Oligotrophic lakes tend to be geologically young, low productivity lakes and eutrophic lakes are older, highly productive ecosystems. Eutrophication of surface waters can be accelerated by an increased input of nutrients, which can limit water use for fisheries, recreation, industry, or drinking. Although nitrogen and carbon are associated with eutrophication, most attention has focused on phosphorus inputs because of the difficulty in controlling the exchange of nitrogen and carbon between the atmosphere and water, and fixation of atmospheric nitrogen by some blue-green algae. Thus, phosphorus often limits eutrophication and its control is of prime importance in decreasing accelerated eutrophication (Sharpley, 1993; Daniels et al., 1994). Of the major nutrients, phosphorus is the most effectively controlled using existing engineering technology and land use management (Reckhow et al., 1980).

The Ecological Endpoints

Ecological risk assessments must have clearly defined endpoints that are socially and biologically relevant, accessible to prediction and measurement, and susceptible to the hazard being assessed (Suter, 1990). A risk assessment using ecosystem-level effects involves the assessment of endpoints that are ecosystem properties. Appropriate endpoints might be the probability of eutrophication or functional properties such as primary productivity (Suter, 1993). Two distinct types of endpoints, assessment and measurement, have been identified by Suter (1990). A measurement endpoint is a measurable environmental characteristic that is related to the socially valued characteristic chosen as the assessment endpoint. In this study, the assessment endpoint for phosphorus is eutrophication, or level of primary productivity, where the measurement endpoint is chlorophyll *a* concentration which, in turn, can be related back to eutrophication (Vollenweider, 1968). Chlorophyll *a*, as the dominant photosynthetic pigment in phytoplankton, is often measured as an indicator of phytoplankton biomass. Many methods have been proposed in the literature for relating in-lake chlorophyll *a* concentrations to trophic state (Sakamoto, 1966; Vollenweider, 1968, 1982; Dobson et al., 1974; Gakstatter et al., 1974). Herein, I utilize two different methods, Gakstatter et al. (1974) and Vollenweider (1982), in order to illustrate a fixed boundary and open boundary system, respectively.

Uncertainty Analysis

Definition, Purpose, and Types of Uncertainty

The American Heritage Dictionary (Morris, 1978) defines uncertainty as "the condition of being in doubt." In most water quality assessments and/or modeling activities the only thing we are sure of is that we are "in doubt." Unfortunately, in most applications, parametric models are treated as deterministic, producing the same outputs for a given set of inputs (Haan, 1989). Uncertainty in spatial data has been greeted by a conspiracy of silence (Rejeski, 1993) and few, if any, existing pollutant transport and fate models include thorough uncertainty analyses (Suter, 1993; Reckhow, 1994). Model uncertainty and error analysis are major, but poorly understood aspects of risk assessment and modeling (Beck, 1987; Summers et al., 1993). We must learn to live with uncertainty and incorporate it into numerical analysis and modeling, rather than ignore it (Fedra, 1983). Rejeski (1993) referred to "modeling honesty" as the truthful representation of model limitations and uncertainties. Reckhow (1994) suggested that *all* scientific uncertainties must be estimated and included in ecological risk assessment or modeling activities.

Many types of uncertainties have been identified in the literature utilizing various taxonomic breakdowns. Brown and Barnwell (1987) described uncertainty inherent in water quality modeling in terms of spatial and temporal variability, sampling error, analytical error, and bias in measurement and estimation techniques. Tung and Mays (1980) defined four main types of uncertainty that exist in designing hydraulic structures: hydrologic (stochastic), hydraulic, structural, and economic. Each of these major categories was further divided into inherent (stochastic), parameter (lack of perfect information), and model (lack of perfect information, equation errors) uncertainty.

Bogardi and Bardossy (1987) acknowledged the importance of incorporating spatial and temporal stochasticity into watershed management. However, they only considered temporal stochasticity in their study. Gardner and O'Neill (1983) discussed three main sources of uncertainty in water quality modeling: assumptions in model construction; measurement errors; and errors in formulating processes. They further discussed measurement errors in terms of parameter variability and divide them further into natural variability and error in parameter estimation.

Fedra (1983) discussed system variability (stochastic), theoretical background (lack of knowledge), environmental database (lack of good data; wrong variables, different places and times), and model uncertainty (simplifications such as lumping and assumptions) as important components of uncertainty. Haan (1989) and Vicens et al. (1975), in discussing uncertainty in hydrologic models, classified uncertainty into three categories:

1. The inherent variability in natural processes.
2. Model uncertainty.
3. Parameter uncertainty.

Rejeski (1993) identified three types of spatial uncertainty that are important when using a GIS for model input: locational error; error due to the aggregation of data (lumping); and fuzzy boundaries (there are virtually no hard boundaries, just transition zones). Antenucci et al. (1991) described locational error as positional accuracy.

Suter et al. (1987) proposed a taxonomy of uncertainty (fig. 1.2). Defined uncertainty is uncertainty about the state of the world and undefined uncertainty relates to one's actual level of ignorance. Undefined uncertainty (also referred to as the unknown unknowns) cannot be incorporated into risk assessment, but its existence must be acknowledged (Suter et al., 1987). Defined uncertainty is further partitioned into identity and analytical uncertainty (fig. 1.2). Identity uncertainty, referring to lack of knowledge concerning the identity of future victims, is a major concern in human risk assessments, but of minor importance in ecological risk assessments. They noted that analytical error is invariability large in ecological analysis and its consideration is essential. The three sources of analytical uncertainty are errors resulting from our conceptualizations of the world (model error), stochasticity in the natural world, and uncertainties in measuring model parameters (parameter error).

Categorization of uncertainty into objective and subjective uncertainty is also common (Palisade Corporation, 1993). Objective uncertainty is due to the stochastic nature of the world while subjective uncertainty is due to lack of knowledge and can always be refined. Similarly, Helton (1994) listed two types of uncertainty: 1) subjective (due to lack of knowledge) and 2) stochastic (due to system variance). MacIntosh et al. (1994) defined these major types of uncertainty as knowledge uncertainty and stochastic variability (fig. 1.3). Knowledge uncertainty is due to incomplete understanding or inadequate measurement of system properties. This uncertainty is a property of the analyst and can also be considered subjective uncertainty (Helton, 1994). Knowledge uncertainty can be further partitioned into model and parameter uncertainty. Stochastic variability is due to unexplained random variability of the natural environment and is a property of the system under study. Stochasticity can be further subdivided into temporal and spatial variability. The terminology of MacIntosh et al. (1994) will be utilized throughout this study (fig. 1.3). Note that this taxonomy is meant for organizational and discussional purposes rather than as a strict categorization of uncertainty types.

Propagation of Uncertainty

There are two main categories of methods for estimating the uncertainty in model predictions: first-order variance propagation and Monte Carlo simulation methods (Beck, 1987; Summers et al., 1993; Zhang et al., 1993). First-order variance techniques have a number of theoretical shortcomings that reduce their utility (Summers et al., 1993). For example, first-order analysis is restricted by assumptions of linearity and the magnitudes of input parameter variances (Gardner and O'Neill, 1983; Summers et al., 1993). First-order approximation deteriorates if the coefficient of variation of the model parameters is greater than 10-20% (Zhang et al., 1993).

Monte Carlo simulation is a method for numerically operating a complex system that has random components (Brown and Barnwell, 1987). Repeated simulations are performed with the model using randomly selected parameter values. At the beginning of each simulation, parameter values are chosen from pre-determined probability distributions. The process is repeated for a number of iterations sufficient to converge on an estimate of the probability distribution of the output variables (Gardner and O'Neill, 1983). Unlike first-order analysis, the validity of Monte Carlo procedures is not affected by nonlinearities or discontinuities in the model (Brown and Barnwell, 1987; Lei and Schilling, 1994). Hammonds et al. (1994) concluded that Monte Carlo simulation is the most robust method for propagating uncertainty through either simple or complex models. Therefore, given the limitations of first-order analysis, Monte Carlo procedures are the preferred method of propagating uncertainty in complex, watershed-level hydrologic and water quality (H/WQ) models (Haan, 1989; Summers et al., 1993; Taskinen et al., 1994; Haan and Zhang, 1995; Prabhu, 1995).

Burmaster and Anderson (1994) detailed principles of good practice for the use of Monte Carlo techniques in human health and ecological risk assessments. They proposed the following principles of good Monte Carlo techniques:

1. Show all formulae used to estimate exposure.
2. Calculate and present point estimates (deterministic) first.
3. Present results from sensitivity analyses of the deterministic calculations to identify the inputs suitable for probabilistic treatment.
4. Restrict probabilistic techniques to important variables.
5. Provide detailed information on the input distributions selected.
6. Show how input distributions capture both variability and uncertainty.
7. Use measured data for selecting input distributions when possible.
8. Discuss the methods and report the goodness-of-fit statistics for distributions fit to measured data. If measured data are not used, discuss the techniques used for judgement.
9. Discuss the presence or absence of correlation between input parameters. If correlations are suspected but no data are available, try Monte Carlo simulations with correlations set to zero and set to values considered high but plausible to learn if possible correlations are important in the analysis.
10. Provide detailed information and graphs for each output distribution.
11. Perform probabilistic sensitivity analyses for all key inputs having distributions in the Monte Carlo analysis in such a way as to distinguish the effects of variability from effects of uncertainty.
12. Investigate and demonstrate the numerical stability of output distributions. The analyst should run enough iterations to ensure numerical stability of the tails of the output distributions.

13. Present the name and statistical quality of the random number generator used.
14. Discuss limitations of the methods and indicate where additional research or measurements could improve the analysis.

Monte Carlo analysis is usually performed using one of two random sampling processes: simple random sampling and Latin hypercube sampling (LHS). Simple random sampling is less efficient than LHS when the sample size is less than a few thousand (Hammonds et al., 1994). Burmaster and Anderson (1994) suggested using Latin hypercube sampling (LHS) for more efficient sampling. LHS ensures full coverage across the range of sampled variables (Morgan and Henrion, 1992; Burmaster and Anderson, 1994; Helton, 1994; Taskinen et al., 1994). Monte Carlo analysis may be performed in many ways; one may write numerical code or use one of several currently available software packages (Hammonds et al., 1994). Monte Carlo simulations were performed in this study using @Risk Version 3.1a (Palisade Corporation, Newfield, NY) linked with Microsoft Excel Version 5.0 (Microsoft Corporation, Cambridge, MA).

Hammonds et al. (1994) proposed a general approach to uncertainty analysis that included the following steps:

1. Define endpoint.
2. List uncertain parameters.
3. Specify the maximum range of uncertain parameters.
4. Specify subjective distributions for values within ranges.
5. Determine and account for correlations.
6. Propagate the uncertainty (analytically or numerically) to produce stochastic output.

7. Derive quantitative statements of uncertainty for the endpoint.
8. Rank parameters contributing to output uncertainty using sensitivity analysis.
9. Obtain additional data for the parameters found to be most important and repeat steps 3 through 8.
10. Present and interpret the results of the analysis.

It is important for an uncertainty analysis to distinguish between stochastic variability and knowledge uncertainty (Burmaster and Anderson, 1994; Hammonds et al., 1994; Helton, 1994; Hoffman and Hammonds, 1994; MacIntosh et al., 1994). Knowledge uncertainty can be improved upon by decreasing the possible range of parameter estimates or by model improvements. A reduction in parameter uncertainty can be accomplished by physically sampling the appropriate phenomena. However, stochastic variability is a natural property of the system being studied and must be accounted for, but can not be reduced.

Helton (1994) and MacIntosh et al. (1994) proposed an uncertainty propagation methodologies which involved two-phase Monte Carlo sampling structures used to propagate knowledge and stochastic uncertainty separately throughout analyses. This two-phased Monte Carlo methodology with LHS was utilized throughout this study. Details of the procedure are presented in Chapter 2 and Chapter 3.

Parameter Distributions

In order to perform Monte Carlo simulations, a probability distribution defining the range of possible values must be defined for each uncertain parameter. However, there is limited information on parameter uncertainty terms reported in literature and distributional shape may be difficult to characterize with confidence (Reckhow, 1994). Lei and Schilling (1994) discussed the difficulty in defining probability density functions (PDFs) for input parameters, but suggested that the mean and variance are the most important properties of a random variable and are not difficult to estimate. They also suggested that the actual shape of PDF is of minor importance and utilized uniform, normal, lognormal, triangular, gamma, and Gumbel with no major differences in output PDF.

Gardner and O'Neill (1983) also discuss the lack of information concerning parameter uncertainty in models and that approximations must be made based on the best available information. Under such circumstances, they recommended the use of triangular distributions due to the few parameters needed to define the distributions (mode, maximum, and minimum). These parameters can usually be inferred from the physical process under investigation. Contrary to the conclusions of Lei and Schilling (1994), they concluded that assuming different distribution shapes for parameter uncertainty can have a significant effect on the output distributions.

Although distributions may result directly from data obtained from a proper experimental design, usually subjective judgment must be used to reflect the degree of belief that the unknown value for a parameter lies within a specified range (Hammonds et al., 1994). Where data are limited and uncertainty is low, Hammond et al. (1994) recommended the specification of a range to define a uniform distribution. If there is knowledge about a most likely value or midpoint, in addition to range, a triangular distribution may be assigned. When range exceeds a factor of 10, log-uniform or log-triangular distributions are prudent. When there is doubt about subjectively defined distributions, the effects should be analyzed (Hammonds et al., 1994). They stated that under no circumstance should an uncertain parameter be held constant simply due to lack of data to define a range or distribution.

Fedra (1983) analyzed uncertainty in a lake ecosystem model for modeling a lake's trophic state or water quality. If data were available, the mean and variability were defined. For the other parameters, he estimated ranges from the literature; the additional uncertainty of these estimates was reflected as wide ranges. He used uniform PDFs for all parameters in his Monte Carlo simulations.

It is important to account for correlations between input distributions during error propagation to ensure realistic results (Reckhow, 1994). However, little experimental data exist concerning the correlation structures within watersheds (Sharma and Rogowski, 1985). Morgan and Henrion (1992) suggested that assessing correlation by subjective judgment is difficult at best. Unfortunately, due to a lack of data, correlations often must be assigned subjectively. In this study, a distribution-free rank correlation methodology (Iman and Conover, 1982) was employed by the @Risk software and correlation coefficients ranging from -1 to 1 were assigned subjectively to dependent variable pairs.

Concluding Remarks

Although extensive research has been conducted concerning the propagation of uncertainty in mathematical models (Beck, 1987; Suter et al., 1987; Haan, 1989; Beven and Binley, 1992; Morgan and Henrion, 1992; Summers et al., 1993; Reckhow, 1994; Helton, 1994; MacIntosh et al., 1994), there are still questions that need to be answered in order to appropriately incorporate uncertainty into H/WQ models at the watershed level. For instance, when evaluating parameter uncertainty using Monte Carlo simulation procedures we often subjectively assign probability distribution types to input parameter values. Is this subjective assignment of parameter distribution shape appropriate? How does the assumed shape affect the output distributions? Additionally, many H/WQ models are distributed-parameter models that perform under the assumption that the physical system is made up of small, uniform, and discrete sub-units (Tim, 1995). Each discrete sub-unit is characterized by a uniform set of properties and input parameters. When performing Monte Carlo procedures on spatially distributed models, do we reduce the variability of the output simply by sub-dividing the study area into multiple units?

The Model

The Need for Simple Models

Beck (1987), in reviewing the analysis of uncertainty in water quality modeling concluded that many of the larger, more complex water quality models can easily generate predictions with little or no confidence attached. Large mechanistic models are too complex and large to be subjected to adequate uncertainty analysis (Reckhow, 1994). Therefore, Reckhow (1994) suggested the use of simpler models with thorough uncertainty analysis. State and regional agencies are a large percentage of model users and they rarely use large mechanistic models. Many modelers believe that since the world is complicated, then simulation models must also be complicated to be accurate.

Suter et al. (1987) suggested that assessment models should be as simple as possible while also including the critical components and processes. Increasing the complexity of a model is often viewed as a desirable goal. However, increased complexity of process models increases the number of parameters and, thereby, increases the potential for parameter error. In fact, increased model complexity can result in more variability in output distributions and increase the chance of incorrectly estimating risk (Suter et al., 1987). This phenomena is referred to as the *Information Paradox* (Rowe, 1977): the more complex one's model becomes, the greater one's uncertainty will be because of the greater number of parameters to be estimated and the greater number of stochastic processes and model functions that must be included.

EUTROMOD

EUTROMOD is a computer model developed to provide guidance and information for managing eutrophication in lakes and reservoirs (Reckhow et al., 1992). It is a collection of spreadsheet-based nutrient loading and lake response models which may be used to relate water quality goals to allowable nutrient inputs. The model, thereby, provides information concerning the appropriate mix of point source discharges, land use, and land management controls that result in acceptable water quality.

EUTROMOD predicts lake-wide, growing season average conditions as a function of annual nutrient loadings (phosphorus and nitrogen). The annual loadings are simulated with a simple, lumped watershed modeling procedure which includes the Rational Equation's runoff coefficient for surface runoff (Chow et al., 1988), the Universal Soil Loss Equation (USLE) for estimating soil loss (Wischmeier and Smith, 1978), loading functions for nutrient export from NPSs, and user provided point source information. Model input requirements are detailed for the original model and a modified version in Chapters 2 and 4, respectively.

Lake response is predicted by a set of nonlinear regression equations from multi-lake regional data sets. These regression equations are used to estimate lake nutrient levels (mg/l), chlorophyll *a* (μg/l), and Secchi Disk depth (m). As discussed previously, the measurement endpoint of the ecological risk assessment is in-lake chlorophyll *a* concentration which can then be related to the assessment endpoint (trophic state). The in-lake chlorophyll *a* regression model for reservoirs in the six-state region including Oklahoma is:

$$\log_{10}(CHLA) = 2.0 + 0.51\log_{10}(\bar{P}) + 0.23\log_{10}(\tau) - 0.35\log_{10}(z) \tag{1.1}$$

where *CHLA* is annual median in-lake chlorophyll *a* concentration (μg/l), $\bar{P}$ is annual median estimated in-lake phosphorus concentration (mg/l), τ is the hydraulic residence time (yr), and z is the average lake depth (m). Details concerning this equation and the equation for estimating in-lake phosphorus can be found in Reckhow et al. (1992). This equation is presented here to highlight the fact that only phosphorus (not nitrogen) is used to estimate chlorophyll *a* concentration. In addition, the importance of hydraulic residence time and lake depth in this equation becomes apparent later in the study. I used EUTROMOD to simulate annual phosphorus load from point and nonpoint sources as well as resulting lake response in terms of chlorophyll *a*.

The original EUTROMOD allows for minimal uncertainty analysis by providing estimates of model error and hydrologic variability. The model error is provided in terms of lake response estimates plus or minus one standard deviation, which is associated with the error term of the regression models. Year-to-year variability is addressed by utilizing an annual mean precipitation and coefficient of variation to account for hydrologic variability. This hydrologic variability is propagated by utilizing first-order error analysis (Reckhow and Chapra, 1983) and is presented as lake response estimates bounded by 90% confidence limits.

These uncertainty estimates within EUTROMOD are useful; however, for several reasons a more extensive uncertainty analysis must be employed to perform a thorough risk analysis. First, although the model error estimates include some parameter uncertainties (Reckhow et al., 1992), parameter uncertainties are not specifically addressed in a manner that allows for detailed sensitivity analysis. Second, the assumptions required for first-order analysis are most likely violated and, therefore, inadequate for uncertainty propagation in EUTROMOD. Therefore, risk analysis was performed in this study using Monte Carlo techniques rather than uncertainty estimates currently provided within EUTROMOD.

DISSERTATION FORMAT

The research performed in this dissertation is presented as a collection of three journal articles (Chapters 2, 3, and 4). Each article contains an abstract, introduction, literature review, methodology, results, conclusions, and references. The subjects of the articles, their purpose, and the journal to which they have been or will be submitted follow. The journals to which each of these articles were or will be submitted required a different style and, therefore, some of the formatting changes from article to article depending on the style required for the journal to which it is intended. Detailed information left out of the journal articles is presented in the Appendices for each article separately. Finally, recommendations for future research are presented.

A two-phased Monte Carlo simulation methodology for use in conducting a total maximum daily load (TMDL) analysis of phosphorus to Wister Lake is presented in the first article (Chapter 2), *Risk Analysis of Total Maximum Daily Loads in an Uncertain Environment Using EUTROMOD*. Previously, a TMDL was conducted for Wister Lake using EUTROMOD in a deterministic manner (Hession et al., 1995). The EUTROMOD model was converted from a shareware spreadsheet program to Micosoft Excel Version 5.0. In Excel, the model is a three-dimensional spreadsheet that is more organized and functional than the original model. The Wister Lake watershed was simulated as a single watershed and watershed-level inputs were lumped by land use. In addition, all input parameters were considered to be uncertain (66 in all) and included in the propagation of uncertainty. Details of the procedures for assigning parameter assignments are presented in Appendix 1 due to lack of space in the journal article. In addition, model simulation results were compared to in-lake monitoring data which are presented in detail in Appendix 1. This article has been submitted to the *Lake and Reservoir Management* journal, and the authors are W.C. Hession, D.E. Storm, C.T. Haan, K.H. Reckhow, and M.D. Smolen.

Various aspects of the two-phased Monte Carlo simulation methodology are evaluated in the second article (Chapter 3) using the Universal Soil Loss Equation (USLE) (Wischmeier and Smith, 1978). This article is titled *Uncertainty and the USLE*. The USLE was selected due to its simplicity, the fact that it is used to estimate soil erosion in EUTROMOD, and extensive observed data were available to compare simulation results with actual data. Twenty-seven years of measured rainfall, runoff, and soil loss data were obtained from the National Soil Erosion Research Laboratory at Purdue University for four original USLE test plots in Guthrie, Oklahoma (data are presented in detail in Appendix 2). These plots were chosen for their close proximity to the Wister Lake study area. The three main goals of this study were: 1) to test effects of subjectively assigning input parameter distributions; 2) to evaluate the effects of distributed parameter modeling (discretization) on output variance; and 3) to illustrate the value of incorporating uncertainty analysis into model studies by comparing probabilistic soil loss estimates to deterministic estimates and observed data. Parameter probability distributions are often subjectively assigned due to a lack of adequate data. Therefore, it is important to determine the effect this subjectivity has on model results. For the final article, EUTROMOD was modified to allow for modeling by subwatersheds, thereby allowing discretization of the watershed. The evaluation of the effect of discretization level on output variance was performed to ensure that the output results for the final portion of the study are reasonable. This article will be submitted to the *Transactions of the ASAE*, and the authors are W.C. Hession, D.E. Storm, and C.T. Haan.

The uncertainty propagation methodology presented in Chapter 2 and a modified EUTROMOD were utilized to perform an ecological risk analysis on Wister Lake for the third and final article (Chapter 4), *A Watershed-Level Ecological Risk Assessment Methodology*. The main differences between this article and the first article were: 1) simulations were performed by subwatershed; 2) a sensitivity analysis was performed (as detailed in Appendix 3) and only parameters significantly contributing to output uncertainty were considered uncertain parameters; and 3) a methodology was presented specifically for performing ecological risk assessments at the watershed-level. The reduction in output uncertainty due to discretization effects was not addressed in this article due to length constraints and the general readership of the journal to which the article has been submitted (the *Journal of Soil and Water Conservation*). However, the reduction in output uncertainty was evaluated and discussed in the Appendix 3. The authors for this final article are W.C. Hession, D.E. Storm, C.T. Haan, S.L. Burks, and M.D. Matlock.

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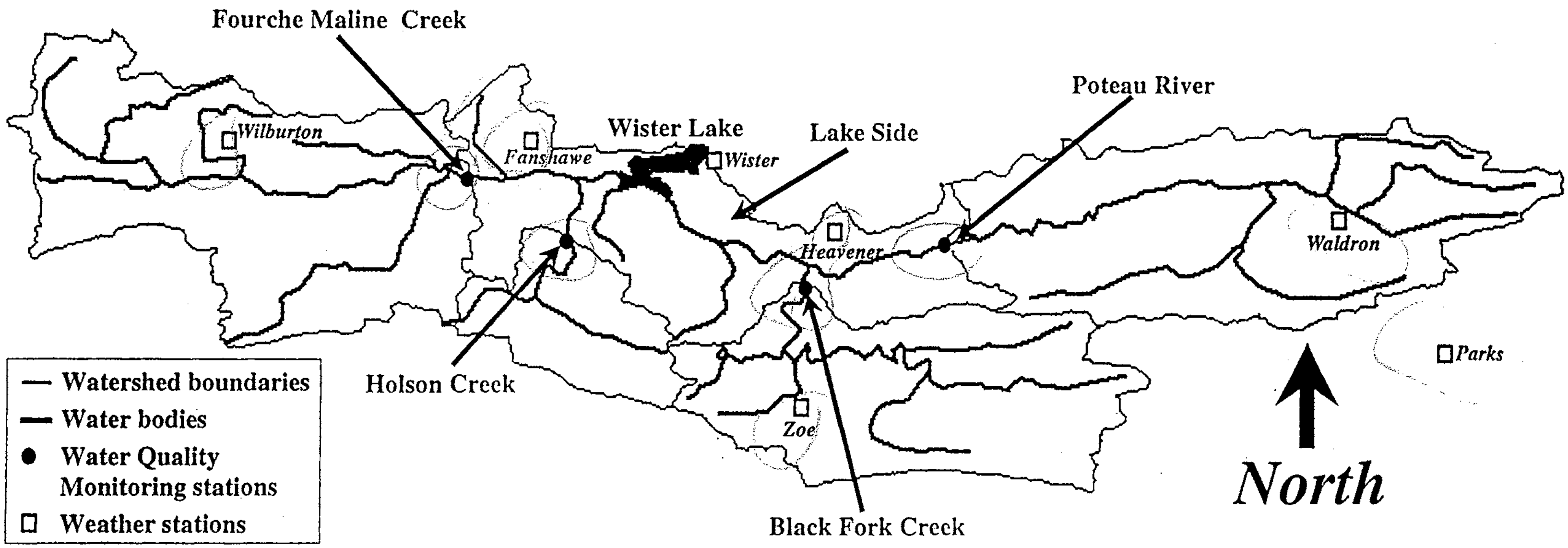

Figure 1.1 Wister Lake watershed with streams, monitoring stations, and subwatersheds identified.

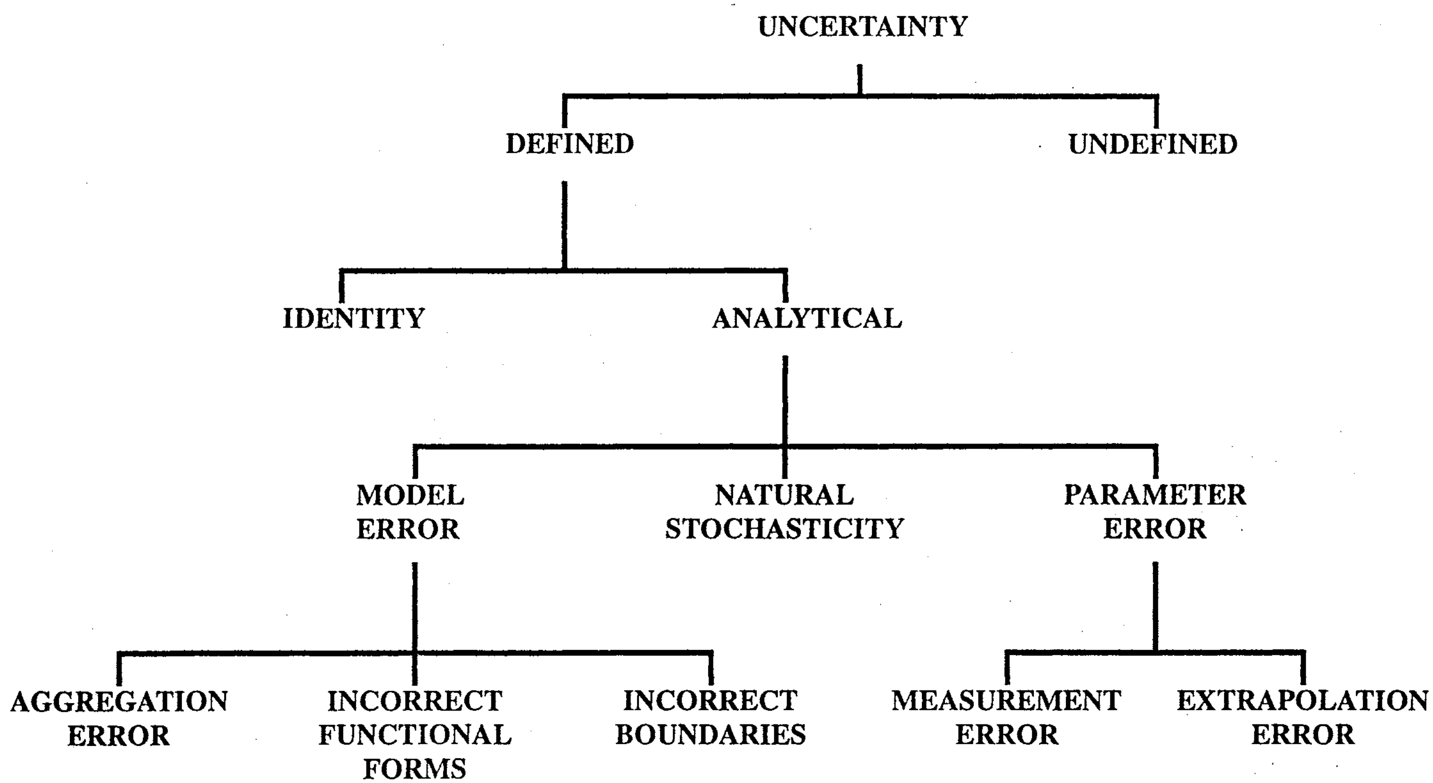

Figure 1.2 Taxonomy of uncertainty proposed by Suter et al. (1987).

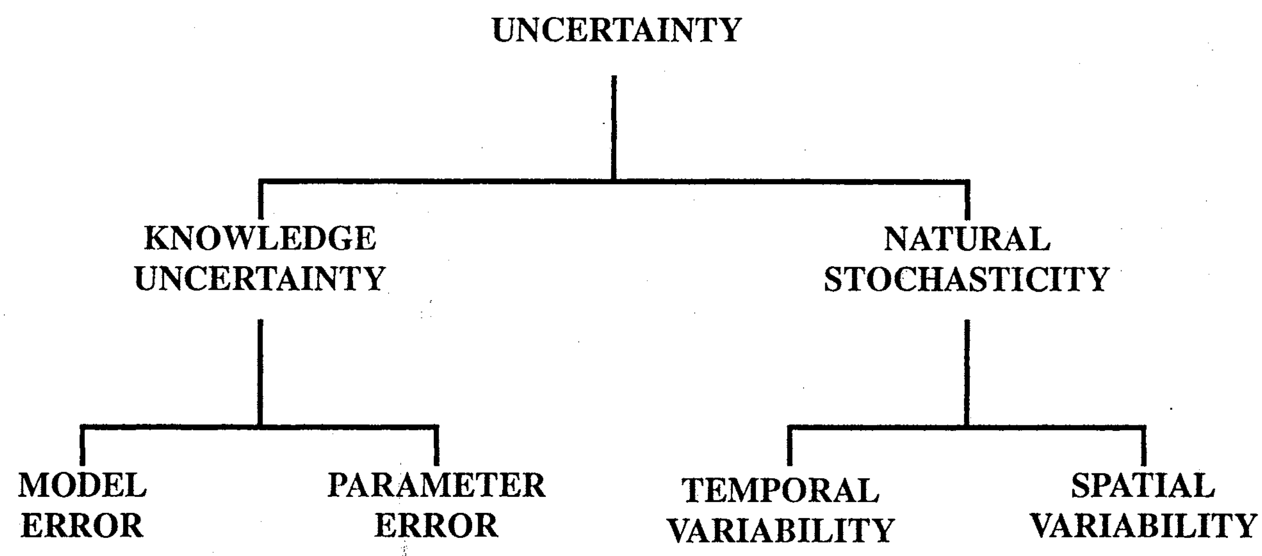

Figure 1.3 Taxonomy of uncertainty utilized throughout this study.

CHAPTER 2

RISK ANALYSIS OF TOTAL MAXIMUM DAILY LOADS IN AN UNCERTAIN ENVIRONMENT USING EUTROMOD

ABSTRACT. *A two-phased Monte Carlo procedure is presented for estimating the probability distribution of annual phosphorus load to a lake and the response of the lake to the load. A watershed-level nutrient loading and lake response model, EUTROMOD, and a geographic information system (GIS) were used. The uncertainty in loading and lake response due to natural variability and parameter uncertainty were propagated separately throughout the analysis. The methodology was applied to Wister Lake in Oklahoma with the lake and its trophic state as the endpoint for total maximum daily load (TMDL) analysis. The watershed contributing to Wister Lake covers approximately 260,000 ha and contains a variety of point and nonpoint sources of pollution contributing to the degradation of the lake. Model results compared well with measured water quality data. EUTROMOD simulations indicated that the lake is eutrophic under current land use and management conditions. Nonpoint source (NPS) pollution was estimated to contribute nearly 90 percent of the annual phosphorus load with the remainder attributed to point sources. The majority of this NPS load was attributed to agriculture. Alternative management evaluations indicated that an average reduction of agricultural*

NPS loads by 25 and 35 percent would be needed to meet our water quality goal with and without point source controls, respectively. Due to uncertainties inherent in the evaluation procedure, the required reductions had large confidence intervals which must be taken into consideration in the decision making process.

INTRODUCTION

Under section 303(d) of the Clean Water Act, States are required to compute total maximum daily loads (TMDLs) for their priority waters. A TMDL is an estimate of the maximum pollutant loading from point and nonpoint sources that a receiving water can accept without exceeding water quality standards (U.S. EPA 1991). The TMDL process has become an important and required portion of U.S. EPA's water quality initiatives.

Although the TMDL requirement has been in existence for 20 years, most implementation has focused on point source (PS) requirements (Zander 1994). Computing a TMDL is difficult for a combination of point and nonpoint pollution sources because of the fundamentally different nature of the two sources. PS loadings are essentially continuous in time, while most nonpoint source (NPS) loadings occur intermittently (Rossman 1991). In reality, the TMDL varies from day to day as a receiving water's capacity to assimilate pollutant loads varies. However, an operational TMDL, where a constant daily load is defined, can be useful in terms of management. The TMDL can be interpreted as the sum of the long-term average loadings from each source category that achieves water quality standards.

Simulation models are often used as an alternative to or in addition to field observations for analyzing and predicting TMDLs (Rossman 1991; Dilks et al. 1993). More often than not, simulations are performed using single point estimates for a model's input variables to predict a single or deterministic output. However, magnitudes and timing of stream flow pollutants are inherently uncertain (Haith 1987). In addition, parameter values used as input to models are only estimates since the actual values are not known with certainty. Rejeski (1993) referred to "modeling honesty" as the truthful representation of model limitations and uncertainties. Beven (1993) and Haan (1995) suggested that the inclusion of uncertainty analysis in modeling activities can be interpreted as intellectual honesty. Reckhow (1994a) suggested that all scientific uncertainties must be estimated and included in modeling activities. However, few, if any, pollutant transport and fate models include thorough uncertainty analyses (Suter 1993; Reckhow 1994a).

We propose a risk-based methodology for conducting TMDLs based on procedures typically utilized in environmental and ecological risk analyses. Risk can be defined as the probability of occurrence of an undesired event (Suter et al. 1987). As an example, we evaluated the risk of eutrophication in Wister Lake as a probabilistic description of uncertain phosphorus inputs. Stream loading and lake response were estimated using EUTROMOD, a watershed-level nutrient loading and lake response model (Reckhow et al. 1992). The uncertainty in loadings and lake response due to natural variability and parameter uncertainty were propagated separately throughout the analysis using a two-phased Monte Carlo simulation methodology.

STUDY AREA

Wister Lake, located in the Arkansas River Basin on the Poteau River, was created by the U.S. Army Corps of Engineers in 1949 to provide flood control, water supply, low flow augmentation, and water conservation. Wister Lake has a surface area of 2,970 ha, a shoreline length of 185 km, a mean depth of 2.3 m, and a maximum depth of 13.4 m at the normal pool elevation of 146 m (Oklahoma Water Resources Board 1990).

Wister Lake is the sole water supply for the majority of residents in LeFlore and three adjacent counties. In addition, the lake and related recreational activities are important to the economy of the area. Wister Lake has been classified as eutrophic since it was surveyed in 1974 by the U.S. EPA (1977) as part of the National Eutrophication Survey. Oklahoma's 1990 Water Quality Assessment Report identifies Wister Lake as eutrophic and highly turbid. In addition, the Wister Lake watershed has been targeted in Oklahoma's section 319 NPS Management Plan as well as in its section 303(d) list of TMDL waters.

The watershed draining into Wister Lake covers approximately 260,000 ha with two thirds in Oklahoma and the remainder in Arkansas (Fig. 2.1). The lake receives pollutants from a wide variety of both point and nonpoint sources. There are nine permitted wastewater treatment plants in Wister Lake's watershed. Nonpoint pollution contributing to the lake includes agricultural, forestry, resource exploration and extraction, and urban sources. A potential major source of nutrients in the watershed originates from a large poultry rearing and processing industry in the region.

The Wister Lake watershed includes portions of the Ouachita Mountains and the Arkansas Valley ecoregions (Omernik 1987). The Ouachita Mountain ecoregion is described as open high hills to open low mountains, land use of oak/hickory/pine woodland and forest, and soils of moist ultisols. The Arkansas Valley ecoregion is described as plains with hills, land use a mix of cropland with pasture and varied forest types of oak/hickory/pine or oak/tupelo/bald cypress, and soils consisting of altisols and sandstone/shale. Land use in the watershed is approximately three fourths forest and one fourth pasture, with small amounts of cropland, urban, and disturbed land. The topography ranges from level flood plains along Fourche Maline Creek and the Poteau River to gently sloping uplands to steep mountainous areas. The relief ranges from Wister Lake's normal pool elevation of 146 m to the 817 m peak of Rich Mountain in Arkansas.

Presently, a cooperative project is underway to prevent further deterioration of water quality in Wister Lake through control of point and nonpoint pollution sources. Monitoring stations have been established throughout the Wister Lake watershed to assist in determining the magnitude of pollutant loading to the lake, distinguishing sources, and tracking the effectiveness of pollution control activities (Hession et al. 1992; Storm et al. 1994). The U.S. Geological Survey and the Oklahoma Conservation Commission have established seven water quality/quantity monitoring stations on the main tributaries flowing to the lake. These are sampled at six-week intervals for flow, nutrients, sediments, and other constituents of concern. Four of these stations have continuous automatic stream flow samplers. In addition, the Oklahoma Water Resources Board has been monitoring the lake as part of an U.S. EPA-funded Clean Lakes Project.

METHODS

TMDL Development

A standard TMDL analysis includes the following activities: (1) determine pollutant of interest; (2) estimate the water's assimilative capacity; (3) quantify pollutant loading from all sources; (4) determine total allowable pollutant load; and (5) allocate the allowable loads among different pollutant sources (U.S. EPA 1991). Quantitatively, a TMDL is defined as:

$$LC = WLA + LA + MOS \tag{2.1}$$

where *LC* is the loading capacity of the receiving water, *WLA* is the waste load allocation or amount of loading capacity allocated to point sources, *LA* is the load allocation attributed to nonpoint sources (natural and anthropogenic), and *MOS* is a margin of safety. The margin of safety is a required component of the TMDL that accounts for uncertainty in pollutant loads and receiving water quality.

It is important to note that the U.S. EPA allows flexibility when describing TMDLs (Zander 1994). TMDLs can be set as actual loadings in mass per day or as concentrations. In addition, in some cases the pollutant or system being investigated may not lend itself to a mass per day limitation, but may best be described in a TMDL as a percentage reduction from current loadings (Zander 1994).

Our risk-based TMDL methodology was derived by combining the steps listed above for a typical TMDL analysis and an approach discussed by Hammonds et al.

(1994) for conducting uncertainty analysis in risk assessments. The general steps are:

1. Define assessment endpoint and determine pollutant of concern.
2. Select model(s) for estimating the water's assimilative capacity and for determining pollutant loadings from all sources.
3. Estimate pollutant loadings and the water's assimilative capacity under uncertainty.
   a. List all uncertain model parameters.
   b. Specify maximum range of values for each uncertain parameter.
   c. Specify a subjective probability distribution for each uncertain parameter.
   d. Determine and account for correlations among parameters.
   e. Propagate uncertainty (we use Monte Carlo techniques).
   f. Determine sensitive parameters, improve estimates for these parameters, and repeat steps 3a through 3f.
   g. Present stochastic output.
4. Determine allowable pollutant load.
5. Allocate allowable loads and/or evaluate management alternatives.

Assessment Endpoint and Pollutant of Concern

Our assessment endpoint was eutrophication. Eutrophication is generally thought of as a natural aging process of lakes (Masters 1991). However, eutrophication of surface waters can be accelerated by an increased input of nutrients, which can limit water use for fisheries, recreation, industry, or drinking. Although nitrogen and carbon are associated with eutrophication, most attention has focused on phosphorus inputs, because of the difficulty in controlling the exchange of nitrogen and carbon between the atmosphere and water, and fixation of atmospheric nitrogen by some blue-green algae. Thus, phosphorus often limits eutrophication and its control is of prime importance in decreasing accelerated eutrophication (Daniels et al. 1994). Of the major nutrients, phosphorus can be effectively controlled using existing engineering technology and land use management (Reckhow et al. 1980). Due to the importance and manageability of phosphorus, we developed a TMDL for total phosphorus (TP) loading to Wister Lake.

Phytoplankton population or algal biomass has been related to nutrient loading and is often used as an indicator of primary productivity or trophic state of water bodies (Vollenweider 1968). Chlorophyll *a*, as the dominant photosynthetic pigment in phytoplankton, is often measured as an indicator of phytoplankton biomass. Since neither Oklahoma nor Arkansas have set water quality standards for nutrients, we used in-lake chlorophyll *a* estimates as an indicator of whether or not water quality goals were met. This assumes that excessive growth of aquatic plants interferes with desirable water uses. We used a chlorophyll *a* concentration of 10 μg/l, which U.S. EPA's National Eutrophication Survey indicated as the breakpoint between mesotrophic and eutrophic lakes (Gakstatter et al. 1974), as our endpoint or water quality goal and for determining a TMDL for TP.

Selection of the chlorophyll *a* concentration goal allowed us to focus attention in this paper on the predictive models and uncertainty analysis necessary to support decision making. In reality, the selection of water quality goals and endpoints should reflect public values (Reckhow 1994b). Scientists can assess the feasibility of various scientific measures of eutrophication; for example, they can estimate the uncertainty in the endpoints under consideration. However, the public and elected officials (as representatives of the public) should choose the endpoint, based on a meaningful relationship between the endpoint and the use and enjoyment of the lake.

The Model

We utilized a nutrient loading and lake response model, EUTROMOD (Reckhow et al. 1992), to estimate Wister Lake's assimilative capacity, to quantify TP loading from all sources, to determine total allowable pollutant load, to allocate these loads among the different sources, and to evaluate management alternatives. The EUTROMOD computer model was developed to provide guidance and information for managing eutrophication in lakes and reservoirs. It is a collection of spreadsheet-based nutrient loading and lake response models which may be used to relate water quality goals to allowable nutrient inputs. The model, thereby, provides information concerning the appropriate mix of PS discharges, land use, and land management controls that result in acceptable water quality.

Lake-wide, growing season average conditions in a lake are predicted as a function of annual nutrient loadings. Annual loadings are simulated with a simple, lumped watershed modeling procedure which includes the Rational Equation's runoff coefficient for surface runoff (Chow et al. 1988), the Universal Soil Loss Equation (USLE) for estimating soil loss (Wischmeier and Smith 1978), loading functions for nutrient export from NPSs, and user provided PS information. Lake response is predicted by a set of nonlinear regression equations from multi-lake regional data sets. These regression equations are used to estimate lake nutrient levels, chlorophyll *a* concentrations, and Secchi Disk depth.

Currently, EUTROMOD allows for minimal uncertainty analysis by providing estimates of model error and hydrologic variability. The model error is provided in terms of lake response estimates plus or minus one standard deviation (associated with the error term of the regression models). Year-to-year variability is addressed by utilizing an annual mean precipitation and corresponding coefficient of variation to account for hydrologic variability. This hydrologic variability is propagated by utilizing first-order error analysis (Reckhow and Chapra, 1983) and is presented as lake response estimates bounded by 90% confidence limits.

These uncertainty estimates within EUTROMOD are useful, however, for several reasons we felt that a more extensive uncertainty analysis must be employed in order to perform a thorough risk analysis. First, although the model error estimates include some parameter uncertainties (Reckhow et al. 1992), parameter uncertainties are not specifically addressed in a manner that allows for adequate sensitivity analysis. Second, the assumptions required for first-order analysis are most likely violated and, therefore, inadequate for uncertainty propagation in EUTROMOD. Therefore, we performed our risk analysis using Monte Carlo techniques rather than utilize the uncertainty estimates currently provided within EUTROMOD.

Model Input

Data required for simulating basin loadings and lake response include information about climate, watershed characteristics, and lake morphometry (Reckhow et al. 1992). Climate parameters include precipitation and lake evaporation estimates. Several parameters are needed to describe the watershed in terms of land use, soils, and topography. Lake morphometry is described using surface area and mean depth. Required model inputs are listed in Table 2.1. EUTROMOD treats each land use in the simulated watershed as a homogeneous unit. Many of the input parameters are required for each land use (as indicated by a subscript *i* in Table 2.1) and, therefore, the number of input parameters depends on the number of unique land uses simulated.

The pertinent data layers (land use, soils, water bodies, and topography) were compiled for the Wister Lake watershed within the Geographic Resources Analysis Support System (GRASS) geographic information system (GIS) developed by the U.S. Army Corps of Engineers (U.S. Army 1991). All watershed characteristic input parameters were area-weighted by land use category utilizing soil, land use, and topographic digital data layers in the GIS (Hession, 1995).

Uncertainty Analysis

Uncertainty Defined

Uncertainty and error analysis are major, but poorly understood, aspects of risk assessment and modeling (Beck 1987; Suter et al. 1987; Summers et al. 1993).

Uncertainty is "the condition of being in doubt" (Morris 1978). In most water quality assessments and/or modeling activities the only thing we are sure of is that we are "in doubt." Unfortunately, in most applications, parametric models are treated as deterministic, producing the same outputs for a given set of inputs (Haan 1989), thereby, ignoring inherent uncertainties.

Many types of uncertainties have been identified in the literature utilizing various taxonomic breakdowns (Suter et al. 1987; Morgan and Henrion 1992; Helton 1994; MacIntosh et al. 1994). We utilized the terminology of MacIntosh et al. (1994) who defined the major types of uncertainty as knowledge uncertainty and stochastic variability (Fig. 2.2). Knowledge uncertainty is due to incomplete understanding or inadequate measurement of system properties. This uncertainty is a property of the analyst and can also be considered subjective uncertainty (Helton 1994). We further divided knowledge uncertainty into model and parameter uncertainty. Stochastic variability is due to unexplained random variability of the natural environment and is a property of the system under study. Stochasticity can be further subdivided into temporal and spatial variability. Note that the taxonomy shown in Fig. 2.2 was meant for discussion purposes rather than as a strict categorization of uncertainty types. For a more thorough discussion of uncertainty the reader is referred to Suter et al. (1987) and Morgan and Henrion (1992).

It is important for uncertainty analyses to distinguish between stochastic variability and knowledge uncertainty (Burmaster and Anderson 1994; Helton 1994; Hoffman and Hammonds 1994; MacIntosh et al. 1994). Knowledge uncertainty can be reduced by narrowing the possible range of parameter estimates or by improving the model. For example, a reduction in parameter uncertainty can be accomplished by physically sampling the appropriate phenomena. However, stochastic variability is a natural property of the system being studied and must be accounted for, but can not be reduced. MacIntosh et al. (1994) and Helton (1994) accounted for stochastic uncertainty using weather variables, i.e. precipitation, while knowledge uncertainty was accounted for by defining possible ranges and distributions for all remaining model variables.

Propagation of Uncertainty

There are two main methods for propagating uncertainty in models: Monte Carlo methods and first-order analysis (Beck 1987; Summers et al. 1993; Zhang et al. 1993). First-order variance techniques have a number of theoretical shortcomings that reduce their utility (Summers et al. 1993). For example, first-order analysis is restricted by assumptions of linearity and the magnitudes of input parameter variances (Gardner and O'Neill 1983; Summers et al. 1993). First-order approximation deteriorates if the coefficient of variation of the model parameters is greater than 10-20% (Zhang et al. 1993). Therefore, given the limitations of first-order analysis, Monte Carlo procedures are the preferred method of propagating uncertainty in complex, watershed-level models (Haan 1989; Summers et al. 1993; Taskinen et al. 1994; Haan and Zhang 1995; Prabhu 1995).

Our uncertainty analysis followed the methodology of Helton (1994) and MacIntosh et al. (1994) which involved a two-phase Monte Carlo sampling structure used to propagate uncertainty while separating knowledge and stochastic uncertainty. The uncertainty analysis was performed using @RISK Version 3.1a (Palisade Corporation, Newfield, NY) linked with Microsoft Excel Version 5.0 (Microsoft Corporation, Cambridge, MA). The EUTROMOD model was converted from a share-ware spreadsheet program to Excel for use in this study.

We included analysis of parameter knowledge uncertainty and stochastic variability utilizing the two-phased Monte Carlo procedure illustrated in Fig. 2.3. The analysis of stochastic variability was nested within knowledge uncertainty. This was done by performing *k* knowledge simulations, with *s* stochastic iterations within each simulation. Each simulation represented a different set of knowledge uncertain parameters while each iteration within a simulation represented a unique set of stochastic parameters. Random sampling was performed using Latin hypercube sampling (LHS) to ensure full coverage across the range of each sampled variable (Morgan and Henrion 1992; Burmaster and Anderson 1994; Helton 1994).

First, a value was drawn at random from the distribution for each input considered to have knowledge uncertainty. In addition, for parameters having both knowledge uncertainty and stochasticity, a mean and variance were sampled for use in defining the distribution of the stochastic variation of that parameter. Together this set of random values, one for each knowledge uncertain input, defined a simulation scenario. Next, a value was drawn at random from the distribution for each input considered to have stochastic variability. These values, along with the previously defined knowledge uncertain inputs, were used as input to the model, computing a corresponding output value representing one iteration of the simulation scenario. Without changing the values of the randomly drawn knowledge uncertain input parameters, a new value was drawn at random for each of the stochastic inputs and a new output value was computed. This resampling of the stochastic parameters was repeated *s* times resulting in *s* deterministic estimates of output for the simulation scenario. These *s* output results were analyzed statistically resulting in a complementary cumulative distribution function (CCDF) that represented the uncertainty in model results due to stochastic variability for one simulation scenario.

At this point, a new value was drawn at random from the distributions for each of the knowledge uncertain input parameters, representing a new simulation scenario, and, holding these constant, the stochastic variables were again resampled *s* times resulting in a new CCDF. This process was repeated for *k* simulation scenarios. Each iteration resulted in a single estimate of the output, meanwhile, each simulation scenario resulted in a set of *s* simulated outputs and a CCDF. The overall analysis resulted in a distribution of *k* CCDFs. The variation in each CCDF showed the effects of stochastic variability on the model estimates while the distribution of CCDFs represented the effects of knowledge uncertainty.

Parameter Uncertainty

As previously discussed, we incorporated both knowledge uncertainty and stochastic variability into our analysis. Upon investigation, all parameters included as input to EUTROMOD were found to have both types of uncertainty. In addition, stochasticity of most parameters exists in both the temporal and spatial realm. As an example, one of the more important parameters used to predict soil loss in the USLE is the K-factor or soil erodibility. Erodibility values have been defined for many soil types and are often included in soil survey reports (Brinlee and Wilson 1981; Abernathy et al. 1983). In addition, one can use nomographs (Wischmeier and Smith 1978) or tables based on soil characteristics (Stewart et al. 1975) to estimate values for a particular soil texture. Therefore, there is knowledge uncertainty in the fact that we do not know which value is appropriate for use in our model for the soil type in question. In addition, the erodibility, which is often assumed to be an inherent soil property with a constant value has been found to vary spatially within a given soil type (Bajracharya and Lal 1992) as well as temporally (Romkens 1995).

In our analysis, we defined only the variability in annual weather (precipitation and rainfall erosivity) as stochastic parameters. In addition, the mean and coefficient of variation of annual precipitation and rainfall erosivity were treated as having knowledge uncertainty. All remaining parameters were treated as having only knowledge uncertainty.

The probability distributions of the stochastic parameters were based on analysis of approximately 30 years of weather data collected from seven raingages distributed within or near the watershed (Hession, 1995). Statistical analyses were performed on the annual rainfall data from all the stations and all were found to fit a lognormal distribution adequately with each station having a different mean and coefficient of variation. We assigned the range of means and coefficients of variation to the knowledge uncertainty portion of precipitation. Rainfall erosivity distributions were assumed to be lognormal and to have a coefficient of variation of 0.67, as determined from erosion plot studies in Guthrie, Oklahoma using 27 years of rainfall data (Daniel et al. 1943; Risse et al. 1994). Knowledge uncertainty was assigned using the range of isoerodent lines shown to be closest to the Wister Lake watershed on the isoerodent map of Wischmeier and Smith (1978).

The ranges and distributions of the remaining parameters representing knowledge uncertainty were assigned subjectively using a few basic rules. The possible range of each parameter was based on the range of reasonable values found in the literature. The distribution was assumed to be either triangular or uniform. MacIntosh et al. (1994) suggested that if the range of a parameter is greater than a factor of 10, the data should be log-transformed to a logtriangular or loguniform distribution. For this study, however, none of our ranges were greater than a factor of 10. If no site specific data were available for a particular parameter, the uniform distribution was assigned to the range of values. However, if data were available from previous studies in the Wister Lake watershed or nearby, the modes were set based on the site-specific data and a triangular distribution was employed. Detailed information concerning parameter estimates and distributional assignments can be found in Hession (1995).

As part of the TMDL process, we simulated both a baseline of natural background conditions (100% forest) as well as current land use conditions. The number of parameters with knowledge uncertainty was 23 for the natural condition simulations and 66 for the current condition simulations. Recall that many of the parameters are assigned for each land use and, therefore, the number of input parameters varies depending on the number of land uses simulated. Presentation of all 66 parameter ranges and distributions used in the current condition simulations would be too lengthy. However, to illustrate the parameter uncertainties, Table 2.2 contains the distributions assigned for the parameters representing stochastic variability and knowledge uncertainty in the natural condition simulations. Detailed information concerning parameter estimation procedures, ranges, and distributions for the current condition simulations can be found in Hession (1995).

It is important to account for correlations between input distributions during error propagation to ensure realistic results (Reckhow, 1994a). A distribution-free rank correlation methodology (Iman and Conover 1982) is employed by the @Risk software, and correlation coefficients ranging from -1.0 to 1.0 were assigned subjectively to dependent variable pairs. The stochastic variables, precipitation and the USLE rainfall erosivity factor (R), were correlated at 1.0 based on analysis of the 27 years of measured data from Guthrie, Oklahoma.

Several parameters with knowledge uncertainty were also assumed to be correlated. The mean precipitation and rainfall erosivity values with knowledge uncertainty were also correlated at 1.0. Lake area and lake depth were assigned a correlation coefficient of 1.0 based on available reservoir storage/depth relationships from the U.S. Army Corps of Engineers. Finally, all trapping factors (five were assigned, one for each of the main subwatersheds flowing into the lake and one for the area flowing directly into the lake, see Fig. 2.1) were correlated subjectively at 0.50. The correlations among the remaining parameters were assumed to be negligible.

RESULTS AND DISCUSSION

Current Conditions

We applied EUTROMOD to the Wister Lake watershed for current conditions. Seven distinct land uses were identified and model input parameter distributions were assigned. The land use types and approximate percentage coverage were: forest (75%), pasture (18-22%), manured pasture (1-4%), urban (1%), water/wetlands (1%), cropland (<1%), and disturbed land (<1%). The land use areas were considered deterministic (known) values except for those of pasture and manured pasture.

The effects of the poultry industry in the watershed were incorporated into the model by estimating the amount of pasture land being spread with poultry litter based on estimates of number of birds, waste produced, and application rates. This manured pasture was then included as a separate land use in the model with higher nutrient loading factors. The resulting estimates were treated as being uncertain by treating the amount of pasture spread with poultry litter as having knowledge uncertainty. However, we assumed that the amount of total pasture land was deterministic. Therefore, the area of manured pasture was selected from a distribution and the remaining pasture land was set equal to the difference between total pasture area and the sampled manured pasture area.

The results of the current condition simulations are shown in Fig. 2.4 through 2.6. The two-phased Monte Carlo procedure described previously was performed with 225 simulations (knowledge uncertainty) with each simulation consisting of 100 iterations (stochastic variability). Sample sizes were based on achieving a 95% confidence of being within 0.5 μg/l of the mean chlorophyll *a*. We used distribution-free confidence intervals (Devore 1987; Morgan and Henrion 1992). The standard statistical technique used to estimate the confidence intervals is applicable to normal Monte Carlo sampling methods (random sampling), however, they are inaccurate for LHS since the samples are not completely independent. Fortunately, the precision estimated is an underestimate of the precision obtained using LHS (Morgan and Henrion 1992).

The distribution of complementary cumulative distribution functions (CCDFs) of median in-lake chlorophyll *a* concentrations resulting from 100 iterations within 225 simulations for current conditions is shown in Fig. 2.4. We showed only 100 of the 225 CCDFs to illustrate the methodology depicted in Fig. 2.3. Recall that each individual CCDF represents stochastic variability using a fixed set of knowledge uncertain parameter values, and the distribution of CCDFs represents the uncertainty due to lack of knowledge. A less congested summary is presented in Fig. 2.5, which provides the expected values and percentile curves of the distribution of CCDFs. The remainder of the results will be illustrated using this summary technique. The stochastic and knowledge expected value curves were obtained by running the model with stochasticity, holding the knowledge variables at their expected values, and with knowledge uncertainty, holding the stochastic variables at their expected values, respectively. A comparison of the two clearly shows that our uncertainty due to lack of knowledge was greater than uncertainty due to stochasticity.

Using the 50th percentile curve, we might estimate that there is a 95% chance that the lake is eutrophic (greater than 10 μg/l). However, further inspection shows that, based on the 5th and 95th percentile CCDFs, the in-lake chlorophyll *a* could range from 8 μg/l to 14.5 μg/l due to knowledge and stochastic uncertainty, resulting in a trophic classification from mesotrophic to highly eutrophic.

A summary of CCDFs for annual total phosphorus load estimates is provided in Fig. 2.6. Our 90% confidence intervals indicated annual loads from below 100 Mg/yr to above 400 Mg/yr. The percentages of total phosphorus load contributions by source are provided in Table 2.3. As with all results of this risk analysis, these percentages were also uncertain and, consequently, they were provided as means bounded by a 90%

confidence interval due to knowledge uncertainty. Simulation results indicate that nonpoint sources contributed the majority of the annual phosphorus loads (with a mean of nearly 90%) and point sources contributed only a small fraction of the annual load. Furthermore, agricultural sources, though accounting for less than 25% of the watershed area, were estimated to contribute nearly 80% of the annual total phosphorus load. It appears that a watershed protection strategy should concentrate on controlling nonpoint pollution sources, especially agricultural, and will require extensive use of best management practices (BMPs) or nutrient management practices (NMPs).

Our main purpose in this study was to present and illustrate a methodology for conducting a risk-based TMDL analysis. Therefore, validation of the model was not of prime importance. However, previous deterministic simulations were performed by Hession et al. (1995a and 1995b) where model results were compared with monitored or previously computed values of runoff, sediment and nutrient loads, and in-lake parameters with favorable results. Although these comparisons were by no means adequate for validation, they did provide some confidence in the simulation process. In addition, in Fig. 2.5 we include 1993 median in-lake chlorophyll *a* estimates for five sampling stations at different locations on the lake as monitored for an ongoing U.S. EPA Clean Lakes Project (Oklahoma Water Resources Board, unpubl. data). Our simulated chlorophyll *a* ranges compare favorably with these monitored values. It is important to remember that the EUTROMOD lake model estimates lake-wide median growing season average conditions. Therefore, it would take many years of measured data, averaged on an annual or seasonal basis to validate the model adequately.

Natural Conditions

Natural loads and lake conditions were estimated by simulating the watershed as 100% forest. The estimate of natural conditions can be considered a reference in the sense that it determines the lowest possible trophic condition that can be achieved through management (Vollenweider 1982). Even though these conditions never existed (the reservoir was not created until 1949, at which time urban and agricultural land uses already existed), these results provide loads and conditions that are natural and, therefore, not due to anthropogenic influences. By definition, natural loads are not pollution and do not have to be mitigated (Griffin et al. 1991).

The estimated median in-lake chlorophyll *a* concentrations under natural conditions are provided in Fig. 2.7. It is interesting to note that, even under these theoretically "pristine" conditions, the lake is predicted to be borderline oligotrophic/mesotrophic based on U.S. EPA's trophic level classification system (4 μg/l; Gakstatter et al. 1974). This is likely due to the fact that Wister Lake is relatively shallow, and shallow lakes tend to be more biologically productive. In fact, many shallow man-made lakes are naturally eutrophic when initially filled (North American Lake Management Society 1988).

Setting the TMDL and Management Alternatives

Our water quality goal was to achieve a trophic state that is borderline mesotrophic/eutrophic corresponding to a chlorophyll *a* concentration of 10 μg/l. The current condition simulations estimated that the lake was eutrophic (Fig. 2.5). Due to the variability and uncertainties involved, there were many approaches that one can take to set the TMDL for total phosphorus. In addition, there was not a set estimate of total phosphorus load for each resulting in-lake chlorophyll *a* output. Due to the sensitivity of the chlorophyll *a* model to variations of lake depth, runoff volume, and hydraulic retention time, a single phosphorus load can result in varied estimates of in-lake chlorophyll *a*. Therefore, instead of setting a total allowable phosphorus load, which is done in traditional TMDL analyses, we instead proceeded directly to evaluating management alternatives. After investigating these management alternatives, we set our TMDL as a reduction in annual total phosphorus loads that will result in the lake being borderline mesotrophic/eutrophic.

Our management alternatives concentrated on control of agricultural loads since they were found to be the most significant source of phosphorus to Wister Lake (Table 2.3). Fig. 2.8 and 2.9 illustrate our approach to determining ways to meet our water quality goals. The resulting in-lake chlorophyll *a* reductions due to percentage reductions in agricultural loads are shown in Fig. 2.8. First, EUTROMOD simulations were performed as deterministic estimates by holding all parameters at their expected value for each 5% increment of agricultural phosphorus load reduction ranging from no reduction to 100% reduction. These deterministic results are presented as the expected value curve in Fig. 2.8. Next, 100 EUTROMOD simulations were conducted for each 5% increment of agricultural phosphorus load reduction, varying only the stochastic parameters. The results are shown as the 90% confidence intervals due to stochastic variability (Fig. 2.8). Finally, 225 EUTROMOD simulations were conducted for each 5% reduction increment while varying only the parameters representing knowledge uncertainty. The results are presented as the 90% confidence interval representing knowledge uncertainty (Fig. 2.8). The wider confidence intervals for knowledge uncertainty indicated that the uncertainty due to lack of knowledge was greater than that due to rainfall stochasticity.

According to the expected value simulation results, we need to reduce annual agricultural loads of total phosphorus by approximately 35% to achieve our water quality goal (shown as the mesotrophic/eutrophic breakpoint line at 10 μg/l in Fig. 2.8). Furthermore, it appears unlikely that an oligotrophic condition can be achieved as was also apparent from our natural or background condition simulations.

The stochastic and knowledge uncertainty 90% confidence intervals can be used to illustrate how uncertain we are in our assessment as well as to set our management strategy with a margin of safety as required for a TMDL analysis (equation 2.1). Based on the stochastic confidence interval, the percentage reduction in agricultural loads required to meet our water quality goals ranged from 30% to nearly 50%. Additionally, the range of reductions was from 0% to more than 70% based on the knowledge uncertainty confidence intervals. These confidence intervals could be used to include a margin of safety by choosing the management option that represents 95% confidence due to stochasticity, i.e. 50% reductions in agricultural loads, or a given confidence in knowledge uncertainty.

The margin of safety was incorporated into the TMDL procedure to provide conservative estimates, however, if one wants to be conservative in the decision making process the degree of conservatism in calculations and decisions should known (Hattis and Burmaster 1994). A stochastic representation as provided by a quantitative uncertainty analysis allows for more useful information for planning and management and can improve decision making (Finkel 1994). Given the stochastic results illustrated above, decisions on the level of management could be made based on probability of occurrence and the level of risk acceptable to resource managers.

To illustrate a management strategy that incorporates both NPS and PS controls, we simulated the results of placing a 2 mg/l phosphorus limit on all point sources in the watershed and proceeded to reduce agricultural NPS in the same manner as discussed above. The results (Fig. 2.9) again illustrated the importance of nonpoint sources of phosphorus to Wister Lake. Implementation of the 2 mg/l limit on point sources with no NPS controls only reduced the most likely chlorophyll *a* value from 11.1 μg/l to just below 10.9 μg/l. Under this scenario a 20% to 35% reduction in agricultural load reductions would still be required based on the stochastic 90% confidence interval or 0% to 63% based on knowledge uncertainty.

Many different combinations of point and nonpoint source controls can be generated to meet water quality goals. Employing NPS controls (BMPs and/or NMPs) is generally cheaper than upgrading or adding wastewater treatment. A cost analysis can be used to determine the most cost-effective combination of controls resulting in watershed-scale pollution control optimization. One innovative management technique is to allow municipalities and utilities to trade NPS control for PS control (Griffin et al. 1991). If trading is allowed, and NPS control is significantly cheaper than additional PS treatment, water quality goals may be more obtainable. There are many different types of NPS controls that can be implemented to achieve water quality goals. However, cost analysis and actual BMP and/or NMP recommendations were beyond the scope of this study.

CONCLUSIONS

Wister Lake, important as a water supply and recreational resource, has been classified eutrophic since 1974. A total maximum daily load (TMDL) for phosphorus was estimated using a nutrient loading and lake response model, EUTROMOD. Model input parameters were evaluated using digital data layers within the GRASS GIS. The TMDL was set such that in-lake chlorophyll *a* concentration estimates remained at levels considered borderline mesotrophic/eutrophic by U.S. EPA estimates (10 μg/l).

The TMDL was described as a percentage reduction from current loads rather than a set allowable phosphorus loading per day. This was due to the fact there was not a set estimate of total phosphorus load for each resulting in-lake chlorophyll *a* output. Due to the importance in variations of lake depth, runoff volume, and hydraulic retention time in determining chlorophyll *a*, a single phosphorus load can result in varied estimates of in-lake chlorophyll *a*. The stochastic output from the model was utilized to incorporate a margin of safety in the TMDL with a known degree of conservatism.

Uncertainty analyses should be a routine part of any TMDL analysis or modeling activity. There are many uncertainties due to the lack of knowledge and system stochasticity that affect model output. Knowledge uncertainty and stochastic variability were evaluated and propagated separately throughout the TMDL analysis. Knowledge uncertainty can be reduced by improving parameter estimates, however, we have little control over the variability of the natural system under study.

It is important to note that the endpoint used in this analysis was also an uncertain entity. Eutrophication itself is a vague term and has different meanings to different people (Shannon and Brezonik 1972). Our endpoint was actually "cultural" eutrophication which refers to the accelerated aging of a lake or reservoir through human activities (Hasler 1947). In addition, we used U.S. EPA's general guideline of 10 μg/l chlorophyll *a* concentration as an indicator of eutrophication. This value is based on measured in-lake concentrations from many lakes and reservoirs as part of the National Eutrophication Survey (Gakstatter et al. 1974). The trophic state of the lakes sampled were determined subjectively through the opinions of the researchers or through comparison with literature values. Vollenweider (1982), in summarizing the results of the Organization for Economic Co-operation and Development's (OECD) Cooperative Program on Eutrophication, recognized the uncertainties involved in using subjective judgement to allocate lakes to trophic categories. He presented the trophic state categories as probability distributions. Therefore, at a given chlorophyll *a* concentration, a given lake would have different probabilities of being classified as oligotrophic, mesotrophic, or eutrophic. We did not utilize Vollenweider's (1982) probabilistic results since the lakes included in his analysis were mostly natural lakes and none were in or near Oklahoma. Reckhow (1979) and Chapra and Reckhow (1979) also discussed the uncertainty inherent in Vollenweider's classification and present methods for incorporating the uncertainty into analysis. Additional work is needed to incorporate this trophic state classification uncertainty into the methodology illustrated in this paper.

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Table 2.1 Input requirements for EUTROMOD.

Type	Parameter		Symbol	Units
Climatic	Precipitation (annual mean)		PREC	cm/yr
	Precipitation (coefficient of variation)		PRECCV	
	Precipitation Nutrients:	Phosphorus	PRECP	mg/l
		Nitrogen	PRECN	mg/l
Watershed	Runoff Coefficient		RC_i	fraction
	USLE Parameters:			
	Rainfall Erosivity		R	MJ-mm/ha-h
	Soil Erodibility		K_i	Mg/ha per unit R
	Topographic Factor		LS_i	ratio
	Cropping Factor		C_i	ratio
	Practice Factor		P_i	ratio
	Area per Land Use		$AREA_i$	ha
	Phosphorus Loading Factors:			
	Dissolved		$LFPDIS_i$	mg/l
	Sediment Attached		$LFPSED_i$	mg/kg
	Phosphorus Enrichment Ratio		ENP	ratio
	Nitrogen Loading Factors:			
	Dissolved		$LFNDIS_i$	mg/l
	Sediment Attached		$LFNSED_i$	mg/kg
	Nitrogen Enrichment Ratio		ENN	ratio
	Trapping Factors		TF_j	ratio
	Septic System Information:			
	Number of People		SEPNUM	per capita-yr
	Phosphorus Load		SEPP	kg P/person-yr
	Nitrogen Load		SEPN	kg N/person-yr
	Phosphorus Soil Retention		RETP	fraction
	Nitrogen Soil Retention		RETN	fraction
	Point Source Information:			
	Waste Flow		PSQ	MGD
	Phosphorus Concentration.		PSP	mg/l
	Nitrogen Concentration		PSN	mg/l
Lake	Surface Area		LAREA	km^2
	Mean Depth		LDEPTH	m
	Lake Evaporation (annual mean)		LEVAP	m/yr

Note: Subscript $_i$ refers to number of land uses and $_j$ refers to number of regions assigned different trapping factors (number of subwatersheds in this case).

Table 2.2 Natural condition parameter distributions.

Type	Parameter	Knowledge Uncertainty	Stochastic Variability
Climatic	PREC	Triangular(112,120,123)[1]	Ln(*k*(PREC)[2], *k*(PRECCV))[3]
	PRECCV	Triangular(0.23,0.25,0.28)	
	PRECP	Triangular(0.012,0.015,0.021)	
	PRECN	Triangular(0.012,0.015,0.021)	
Watershed	RC_{forest}	Triangular(0.10,0.25,0.40)	
	R	Triangular(430,520,600)	Ln(*k*(R) ,0.67)
	K_{forest}	Uniform(0.27,0.43)[4]	
	LS_{forest}	Uniform(1.6,2.8)	
	C_{forest}	Uniform(0.0001,0.001)	
	P_{forest}	*constant*[5]	
	$AREA_{forest}$	*constant*	
	$LFPDIS_{forest}$	Uniform(0.006,0.012)	
	$LFPSED_{forest}$	Triangular(200,300,400)	
	ENP	Triangular(1.19,1.50,3.74)	
	$LFNDIS_{forest}$	Uniform(0.06,0.19)	
	$LFNSED_{forest}$	Triangular(900,1200,2000)	
	ENN	Triangular(1.08,2.00,5.00)	
	$TF_{Poteau\ River}$	Triangular(0.78,0.92,0.97)	
	$TF_{Fourche\ Maline\ Creek}$	Triangular(0.80,0.91,0.97)	
	$TF_{Black\ Fork\ Creek}$	Triangular(0.65,0.90,0.97)	
	$TF_{Holson\ Creek}$	Triangular(0.40,0.86,0.96)	
	$TF_{Lake\ Side}$	Triangular(0.80,0.85,0.97)	
	SEPNUM	--[6]	
	SEPP	--	
	SEPN	--	
	RETP	--	
	RETN	--	
	PSQ	--	
	PSP	--	
	PSN	--	
Lake	LAREA	Uniform(27.11,29.68)	
	LDEPTH	Uniform(1.82,2.59)	
	LEVAP	Triangular(1.0,1.3,1.8)	

[1] Triangular distribution (minimum, mode, maximum).
[2] Value obtained from knowledge (*k*) uncertainty distribution for each simulation scenario.
[3] Lognormal distribution (mean, coefficient of variation).
[4] Uniform distribution (minimum, maximum).
[5] Values assumed constant throughout all simulations and iterations.
[6] Under natural conditions there would be no point sources or septic systems.

Table 2.3 Mean and 90% confidence interval estimates of total phosphorus load by source category as percent of total based on EUTROMOD simulations with knowledge uncertainty.

Estimate	Point Sources (%)	Nonpoint Sources: Agriculture (%)	Nonpoint Sources: Forest (%)	Nonpoint Sources: Other[1] (%)
Mean	11	80	5	4
5th Percentile	6	72	2	2
95th Percentile	17	87	9	7

[1] Includes disturbed land, precipitation, septic systems, and urban/built-up land.

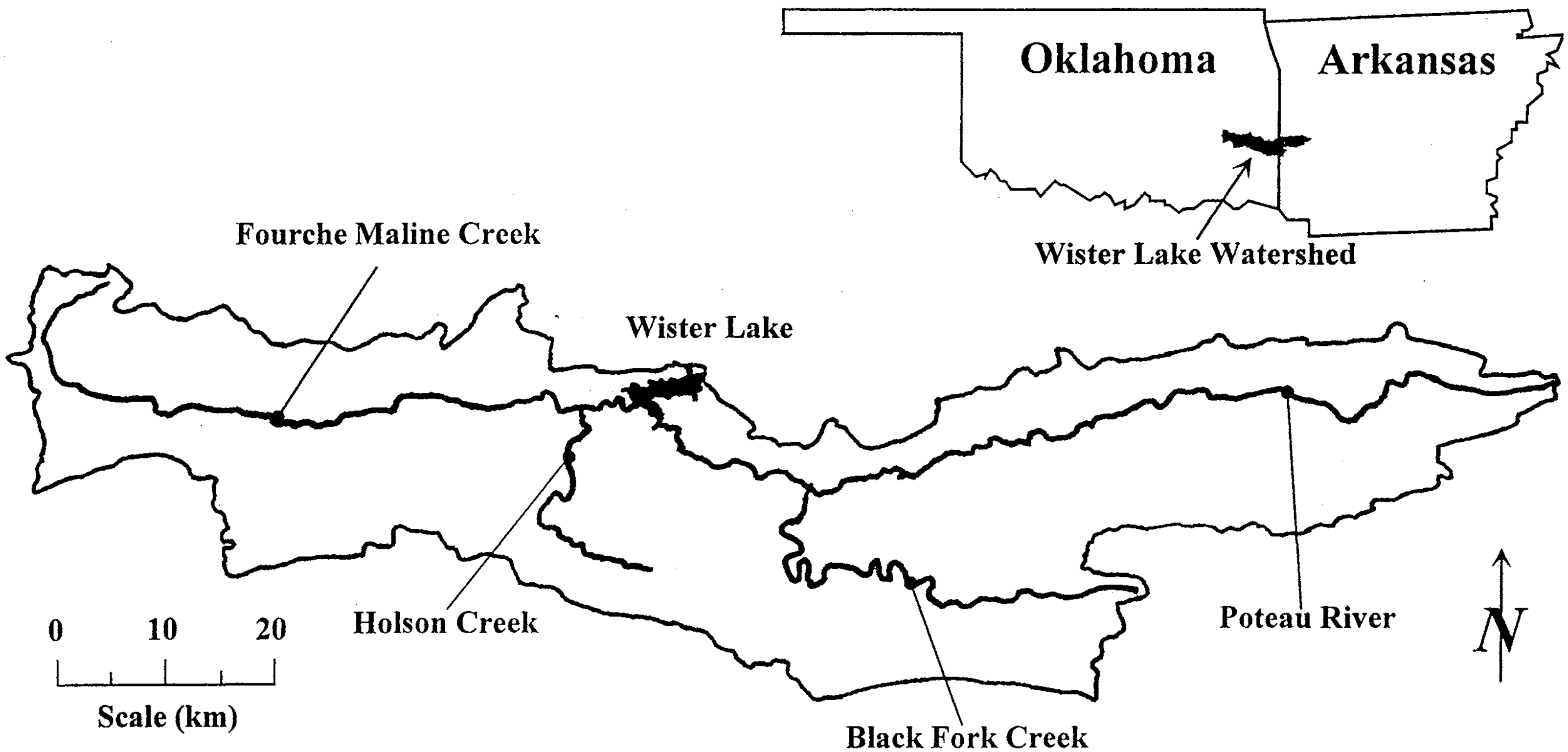

Figure 2.1 Location of Wister Lake watershed with major tributaries.

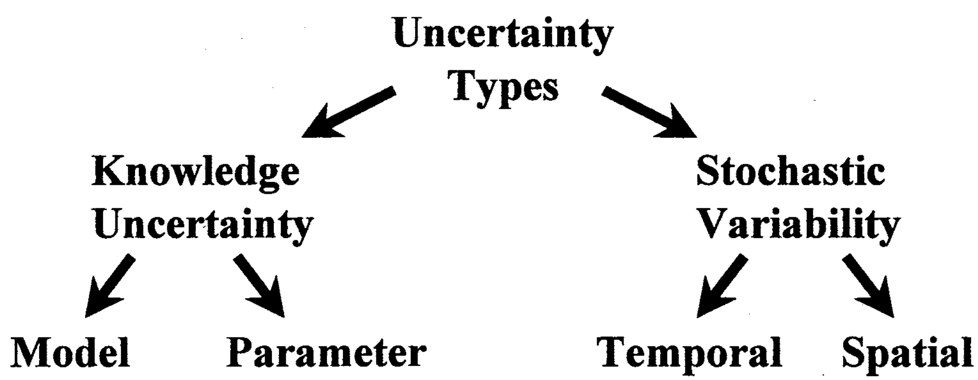

Figure 2.2 Types of uncertainty.

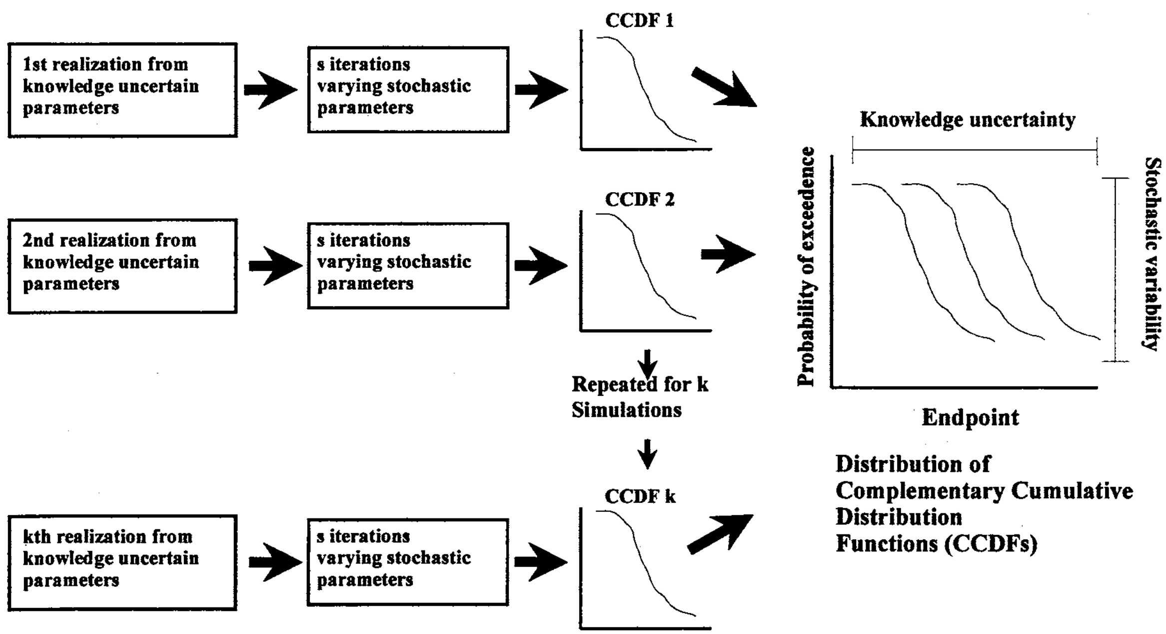

Figure 2.3 Illustration of two-phased Monte Carlo procedure utilized to propagate knowledge uncertainty and stochastic variability separately.

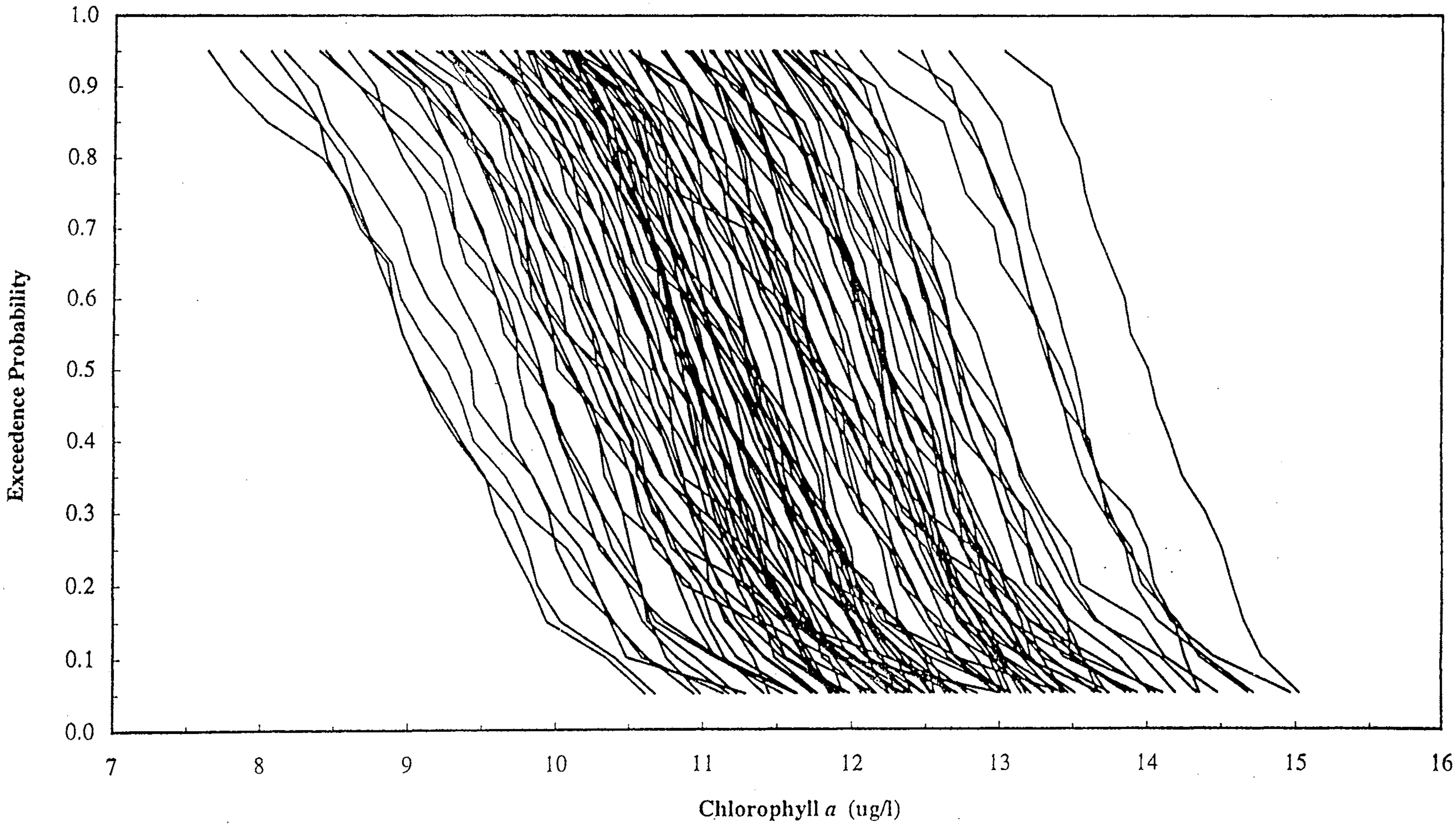

Figure 2.4 Distribution of complementary cumulative distribution functions (CCDFs) for in-lake chlorophyll *a* estimates with EUTROMOD for current conditions.

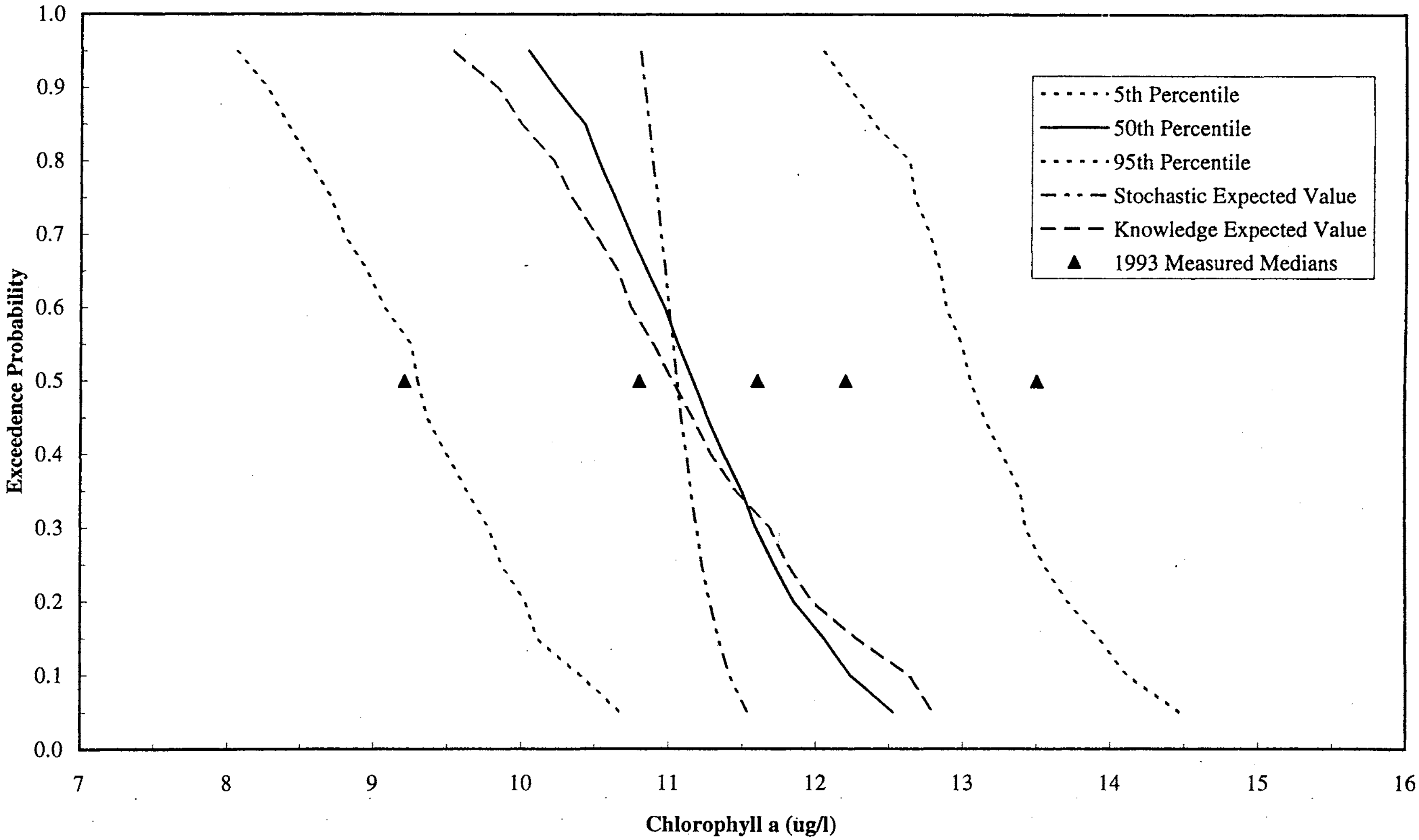

Figure 2.5 Summary of the distribution of CCDFs of in-lake chlorophyll *a* estimates for current conditions.

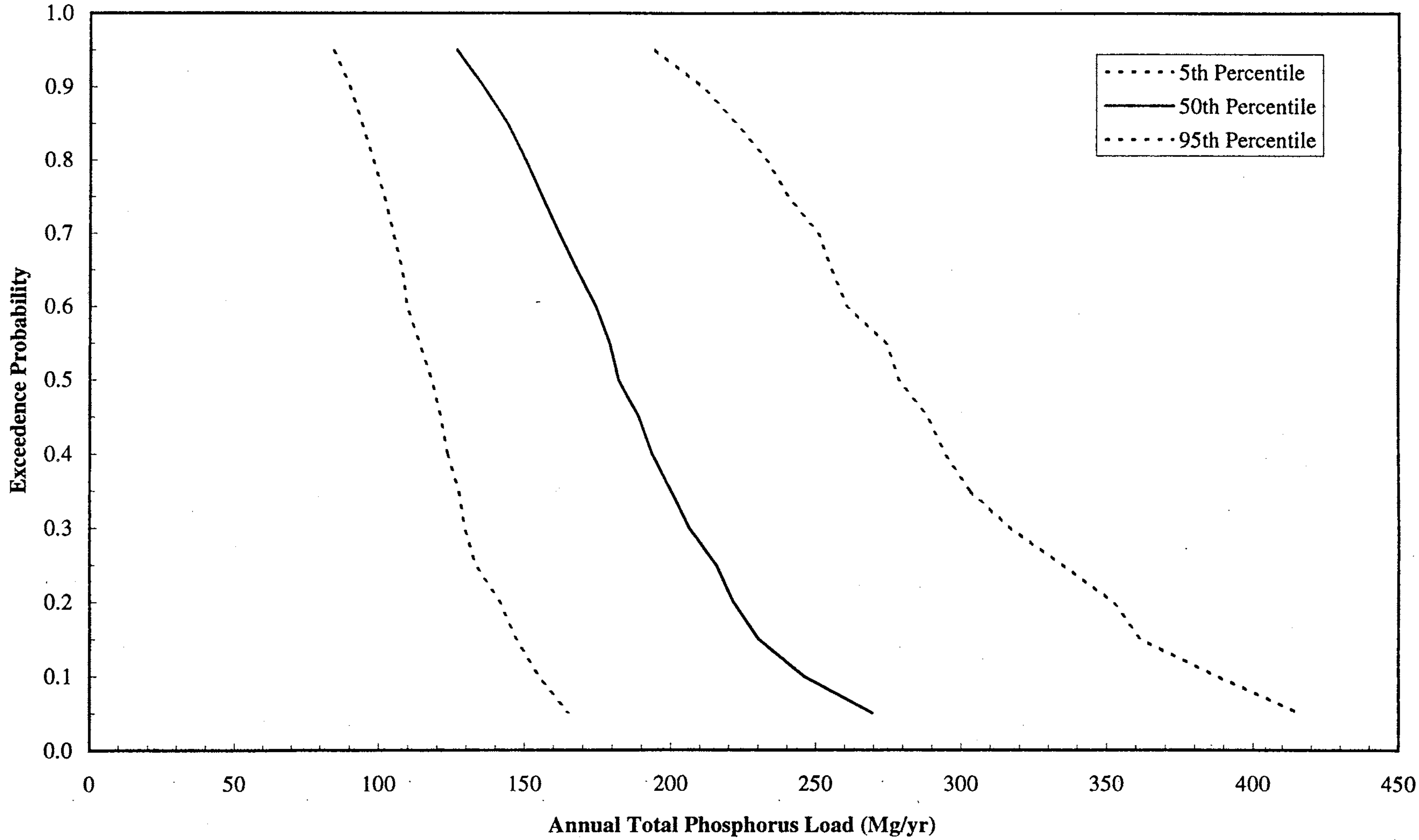

Figure 2.6 Summary of CCDFs of annual total phosphorus load estimates for current conditions.

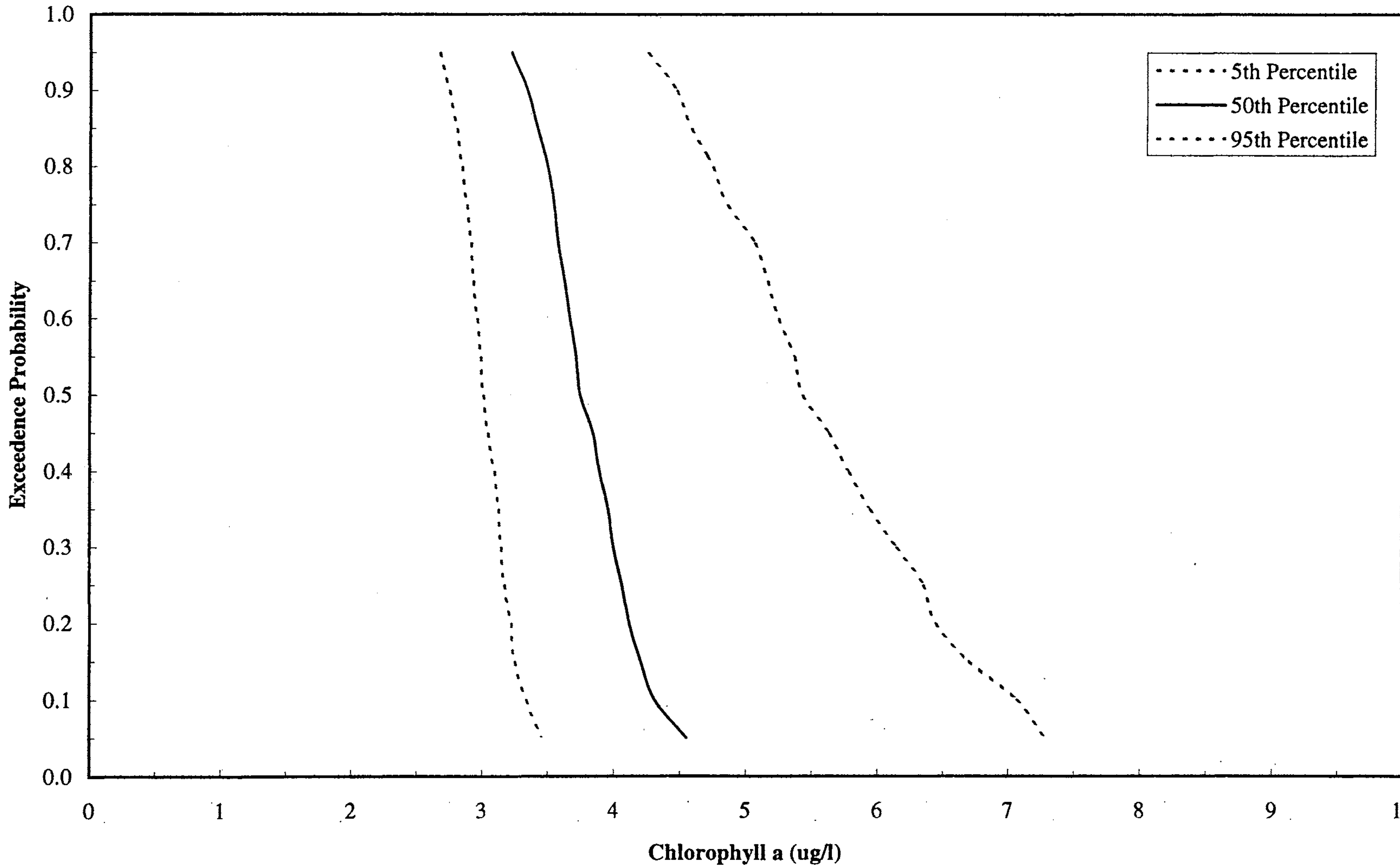

Figure 2.7 Summary of CCDFs of in-lake chlorophyll a estimates for natural conditions.

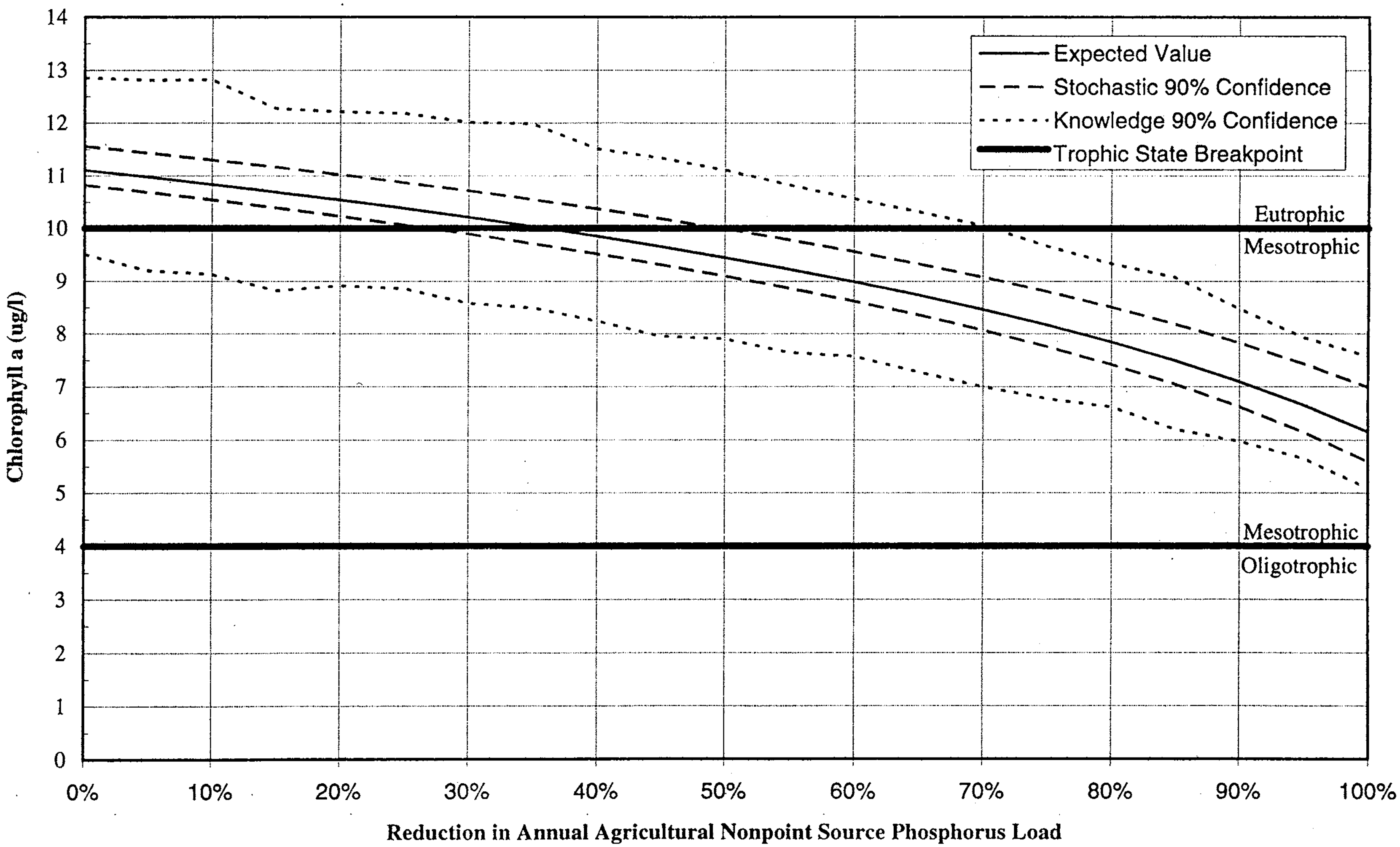

Figure 2.8 In-lake chlorophyll *a* estimates and corresponding trophic state category in response to percentage reductions in annual agricultural nonpoint source phosphorus loads.

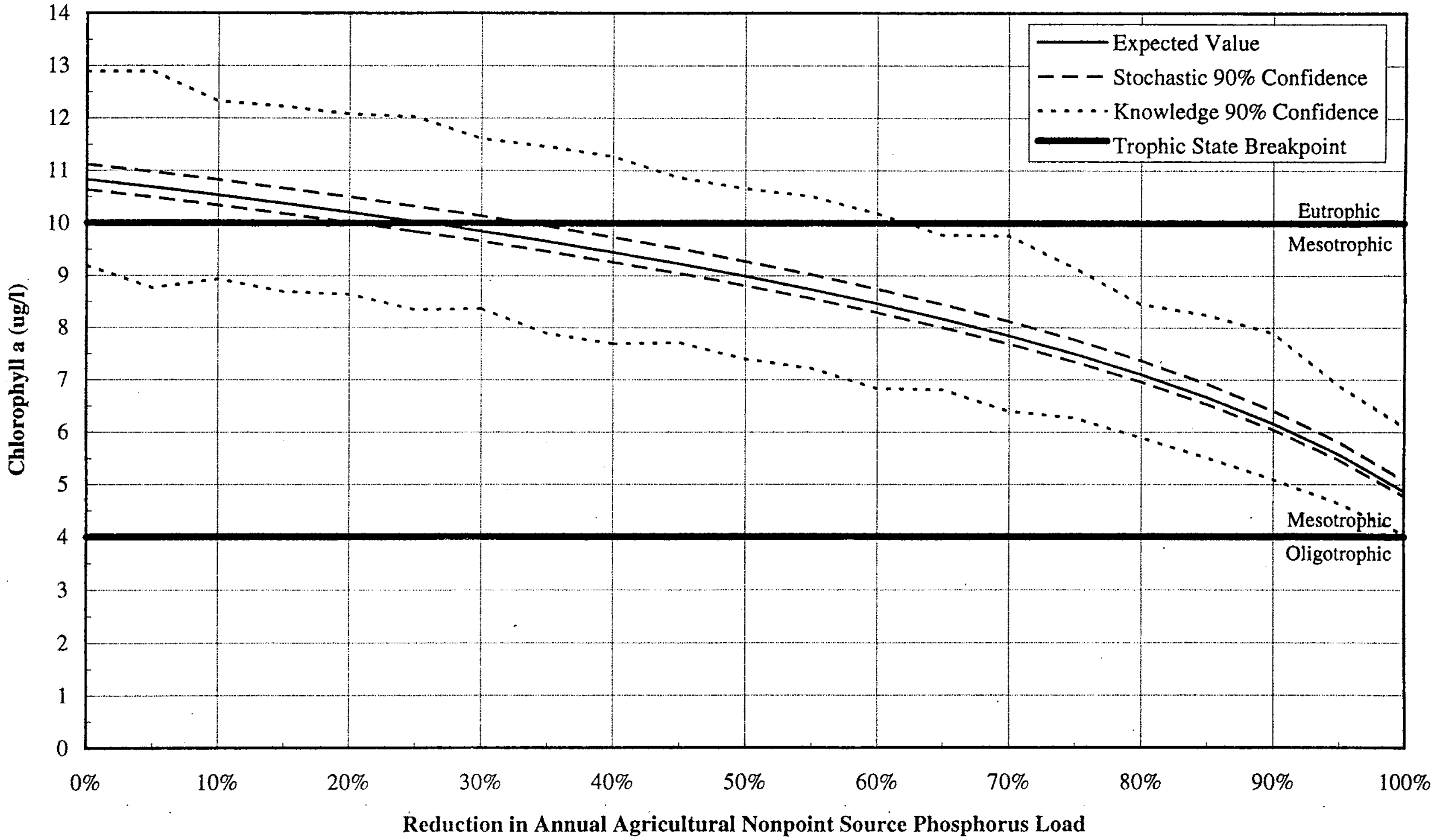

Figure 2.9 In-lake chlorophyll *a* estimates and corresponding trophic state category in response to placing a 2 mg/l phosphorus limit on all point sources as well as reductions in annual agricultural nonpoint source phosphorus loads.

CHAPTER 3

UNCERTAINTY AND THE UNIVERSAL SOIL LOSS EQUATION

ABSTRACT. *Hydrologic and water quality (H/WQ) models are important tools for assessment and management at the watershed level. Typically, simulations are performed deterministically, resulting in a single estimate of the output while ignoring natural variability and knowledge uncertainty. We propose a two-phased Monte Carlo methodology that provides for the evaluation and propagation of natural stochastic variability and knowledge uncertainty separately in H/WQ modeling efforts. The Universal Soil Loss Equation (USLE) and experimental plot data were used to evaluate the proposed methodology and to illustrate the value of incorporating uncertainty analysis into model studies. Next, we showed that subjectively assigning triangular, normal, or lognormal distributional shapes to represent parameter uncertainty has little effect on output variability. However, the uniform distribution, typically used to express greater uncertainty in parameter estimates, resulted in greater output uncertainty. Finally, we determined that output variance is reduced as the level of discretization increases in spatially distributed modeling due to the mathematics of the underlying statistics. Watersheds are often represented as a collection of discrete sub-units in distributed parameter H/WQ models. Therefore, model output uncertainty would be*

under-estimated due to discretization level rather than due to increased confidence in parameter estimates or model improvements. Additional work is needed to develop and test procedures to correct for this artificial reduction in output variance in order to accurately present output variability and uncertainty for distributed H/WQ models.

INTRODUCTION

There is a growing consensus that the water quality problems now facing society can best be solved by following a basin-wide or watershed protection approach (U.S. EPA, 1991a). The Clean Water Act (CWA) of 1987, Section 319, requires that States implement nonpoint source (NPS) management programs to the maximum extent practicable on a watershed-by-watershed basis (U.S. EPA, 1991b). In addition, the present reauthorization of the CWA is expected to incorporate a watershed management approach and may include amendments that provide incentives to state and local governments to adopt watershed management plans (Browner, 1993; Perciasepe, 1994).

Hydrologic and water quality (H/WQ) models are important tools for assessment and management at the watershed level. H/WQ simulation models are often used as an alternative to or in addition to field observations for analyzing and predicting watershed response and for developing watershed management plans. The importance of incorporating uncertainty analysis into H/WQ models has been emphasized by many authors (Beck, 1987; Reckhow, 1994; Haan et al., 1995; Hession et al., 1995a; Kumar and Heatwole, 1995). More often than not, model simulations are performed using single point estimates for a model's input variables to predict a single or deterministic output.

However, magnitudes and timing of stream flow pollutants are inherently uncertain (Haith, 1987). In addition, parameter values used as input to models are only estimates since the actual values are not known with certainty. Rejeski (1993) referred to "modeling honesty" as the truthful representation of model limitations and uncertainties. Beven (1993) and Haan (1995) suggested that the inclusion of uncertainty analysis in modeling activities can be interpreted as intellectual honesty. Reckhow (1994) suggested that *all* scientific uncertainties must be estimated and included in modeling activities. However, few, if any, existing pollutant transport and fate models include thorough uncertainty analyses (Suter, 1993; Reckhow, 1994).

There are two main categories of methods for estimating the uncertainty in model predictions: Monte Carlo methods and first-order variance propagation (Beck, 1987; Summers et al., 1993; Zhang et al., 1993). First-order variance techniques have a number of theoretical shortcomings that reduce their utility (Summers et al., 1993). For example, first-order analysis is restricted by assumptions of linearity and the magnitudes of input parameter variances (Gardner and O'Neill, 1983; Summers et al., 1993). First-order approximation deteriorates if the coefficient of variation of the model parameters is greater than 10-20% (Zhang et al., 1993). Therefore, given the limitations of first-order analysis, Monte Carlo procedures are the preferred method of propagating uncertainty in complex, watershed-level models (Haan, 1989; Summers et al., 1993; Taskinen et al., 1994; Haan and Zhang, 1995; Kumar and Heatwole, 1995; Prabhu, 1995).

We propose a two-phased Monte Carlo procedure for propagating uncertainty in H/WQ models based on procedures typically utilized in environmental and ecological risk analyses (Helton, 1994; MacIntosh et al., 1994). Risk can be defined as the probability of occurrence of an undesired event (Suter et al., 1987). Although extensive research has been conducted concerning the propagation of uncertainty in mathematical models (Beck, 1987; Suter et al., 1987; Haan, 1989; Beven and Binley, 1992; Morgan and Henrion, 1992; Summers et al., 1993; Reckhow, 1994; Helton, 1994; MacIntosh et al., 1994), there are still many questions that need to be answered in order to appropriately incorporate uncertainty into H/WQ models at the watershed level.

For instance, when evaluating parameter uncertainty using Monte Carlo simulation procedures, probability distribution types are often subjectively assigned to input parameter values. Is this subjective assignment of parameter distribution shape appropriate? How does the assumed shape affect the output distributions? Additionally, many H/WQ models are distributed-parameter models that perform under the assumption that the physical system is made up of small, uniform, and discrete sub-units (Tim, 1995). Each discrete sub-unit is characterized by a uniform set of properties and input parameters. When performing Monte Carlo procedures on spatially distributed models, do we reduce the variability of the output simply by sub-dividing the study area into multiple units?

In order to explore these questions, we evaluated our uncertainty propagation methodology using the Universal Soil Loss Equation (USLE) (Wischmeier and Smith, 1978). The USLE was developed as a method of estimating long-term average soil losses in runoff from specific field areas under specified cropping and management practices (Wischmeier, 1984). The USLE groups the many variables and interactions that influence erosion into six major factors, resulting in the following equation:

$$A = R\,K\,LS\,C\,P \tag{3.1}$$

where A is the estimated long-term average annual soil loss per unit area (Mg/ha), R is the rainfall erosivity factor, K is the soil-erodibility factor, LS is a dimensionless topographic factor that represents the combined effects of slope length and steepness, C is the cover and management factor, and P is the factor for supporting practices. Detailed descriptions of the USLE and its factors can be found in Wischmeier and Smith (1978) and Stewart et al. (1975).

Although the USLE is fairly simple and is in the process of being replaced by the new technology of RUSLE (Renard and Ferreira, 1993) and WEPP (Nearing et al., 1989), it is still used extensively for conservation planning. In addition, the USLE and variations of the equation are used in many distributed parameter watershed-scale models such as AGNPS (Young et al., 1989), SWRRB (Williams et al., 1985); SWAT (Srinivasan and Arnold, 1994); SIMPLE (Sabbagh et al., 1995), and EUTROMOD (Reckhow et al., 1992; Hession et al., 1995b). The USLE has also been utilized independently as a spatially distributed model of soil loss (Pelletier, 1985; Hession and Shanholtz, 1988).

It is important to note that, while we compared our USLE estimates to measured soil loss values, this research was not conducted to validate or disprove the USLE. Several comprehensive studies have been conducted concerning the accuracy of the USLE (Wischmeier, 1972; Risse et al., 1993), while others have evaluated the USLE under specific conditions in different locations (Onstad et al., 1976; Kramer and Alberts, 1986). In addition, several studies have treated the USLE in terms of risk and uncertainty, thereby estimating soil loss in a stochastic manner (Fogel et al., 1977; Snyder and Thomas, 1986, 1987; Thomas and Snyder, 1986; Thomas et al., 1988).

Twenty-seven years of measured rainfall, runoff, and soil loss data were obtained from the National Soil Erosion Research Laboratory at Purdue University for four original USLE test plots in Guthrie, Oklahoma. These plots were chosen for their close proximity to other studies currently being conducted in Oklahoma by the authors. The plot data were used to evaluate our proposed two-phased uncertainty propagation methodology and to conduct comparisons between estimated and measured soil loss in order to illustrate the value of incorporating uncertainty analysis into model studies. We also evaluated how different probability distribution assumptions affect output results and how discretization level affects output variance in a spatially distributed model.

METHODS

Study Area

In 1930 the Red Plains Conservation Experiment Station in Guthrie, Oklahoma began a series of soil-erosion investigations (Daniel et al., 1943). Numerous soil-erosion plots and small watersheds were instrumented to collect rainfall, runoff, and erosion data. The data used in this study were from the "control plots" which were incorporated into the analyses resulting in the empirically-based USLE (Wischmeier and Smith, 1978).

We selected the four plots with the longest period of record (27 years from 1930 through 1956) for use in this study. Table 3.1 provides size, slope, tillage, and cropping information for each of the plots. All four plots consisted of a Stephensville fine sandy loam soil. The cotton plots were harvested in the fall, leaving cotton stalks over winter, and spring turnplowed parallel to slope (up and down slope) in the spring. The fallow plot was not tilled regularly and was, therefore, fully consolidated (Risse et al., 1994).

Uncertainty Analysis

Uncertainty Defined

Uncertainty and error analysis are major, but poorly understood aspects of risk assessment and modeling (Beck, 1987; Suter et al., 1987; Summers et al., 1993). Uncertainty is "the condition of being in doubt" (Morris, 1978). In most H/WQ modeling activities the only thing we are sure of is that we are "in doubt." Unfortunately, in most applications, parametric models are treated as deterministic, producing the same outputs for a given set of inputs (Haan, 1989), thereby, ignoring inherent uncertainties.

Many types of uncertainties have been identified in the literature utilizing various taxonomic breakdowns (Suter et al., 1987; Morgan and Henrion, 1992; Helton, 1994; MacIntosh et al., 1994). We utilized terminology used by MacIntosh et al. (1994) who defined the major types of uncertainty as knowledge uncertainty and stochastic variability (fig. 3.1). Knowledge uncertainty is due to incomplete understanding or inadequate measurement of system properties. This uncertainty is a property of the analyst and can also be considered subjective uncertainty (Helton, 1994). We further divided knowledge uncertainty into model and parameter uncertainty.

Stochastic variability is due to unexplained random variability of the natural environment and is a property of the system under study. Stochastic variability can be further divided into temporal and spatial variability. It is important to note that the taxonomy shown in figure 3.1 was meant for discussion purposes rather than a strict categorization of uncertainty types. For more thorough discussions of uncertainty types the reader is referred to Suter et al. (1987) and Morgan and Henrion (1992).

It is important for uncertainty analyses to distinguish between stochastic variability and knowledge uncertainty (Burmaster and Anderson, 1994; Helton, 1994; Hoffman and Hammonds, 1994; MacIntosh et al., 1994). Knowledge uncertainty can be improved upon by decreasing the possible range of parameter estimates or by model improvements. A reduction in parameter uncertainty can be accomplished by physically sampling the appropriate phenomena. However, stochastic variability is a natural property of the system being studied and must be accounted for, but can not be reduced. MacIntosh et al. (1994) and Helton (1994) accounted for stochastic uncertainty using weather variables, i.e. precipitation, while knowledge uncertainty was accounted for by defining possible ranges and distributions for all remaining model variables.

Propagation of Uncertainty

Our uncertainty analysis followed the methodology of Helton (1994) and MacIntosh et al. (1994) which involved a two-phase Monte Carlo sampling structure used to propagate uncertainty while separating knowledge and stochastic uncertainty. The uncertainty analysis was performed using @RISK Version 3.1a (Palisade Corporation, Newfield, NY) linked with Microsoft Excel Version 5.0 (Microsoft Corporation, Cambridge, MA). The USLE was entered into the Excel spreadsheet program for use in this study.

We included analysis of parameter knowledge uncertainty and stochastic variability utilizing the two-phase Monte Carlo procedure illustrated in figure 3.2. The analysis of stochastic variability was nested within knowledge uncertainty. This was done by performing *k* knowledge simulations, with *s* stochastic iterations within each simulation. Each simulation represented a different set of knowledge uncertain parameters while each iteration within a simulation represented a unique set of stochastic parameters. Random sampling was performed using Latin hypercube sampling (LHS) to ensure full coverage across the range of each sampled variable (Morgan and Henrion, 1992; Burmaster and Anderson, 1994; Helton, 1994; Taskinen et al., 1994).

First, a value was drawn at random from the distribution for each input considered to have knowledge uncertainty. Together this set of random values, one for each knowledge uncertain input, defined a simulation scenario. Next, a value was drawn at random from the distribution for each input considered to have stochastic variability. These values, along with the previously defined knowledge uncertain inputs, were used as input to the model, computing a corresponding output value representing one iteration of the simulation scenario. Without changing the values of the randomly drawn knowledge uncertain input parameters, a new value was drawn at random for each of the stochastic inputs and a new output value was computed. This resampling of the stochastic parameters was repeated *s* times resulting in *s* deterministic estimates of output for the simulation scenario. These *s* output results were analyzed statistically resulting in a complementary cumulative distribution function (CCDF) that represented the uncertainty in model results due to stochastic variability for one simulation scenario.

At this point, a new value was drawn at random from the distributions for each of the knowledge input parameters, representing a new simulation scenario, and, holding these constant, the stochastic variables were again resampled *s* times resulting in a new CCDF. This process was repeated for *k* simulation scenarios. Each iteration resulted in a single estimate of the output, meanwhile, each simulation scenario resulted in a set of *s* simulated outputs and a CCDF. The overall analysis resulted in a distribution of *k* CCDFs. The variation in each CCDF showed the effects of stochastic variability on the model estimates while the distribution of CCDFs showed the effects of knowledge uncertainty.

Parameter Uncertainty

We incorporated both knowledge uncertainty and stochastic variability into our analysis. Upon investigation, all parameters in the USLE can be found to have both types of uncertainty. In addition, stochastic variability of these parameters exists in both the temporal and spatial realm. As an illustrative example, consider the K factor or soil erodibility. Erodibility values have been defined for many soil types and are often included in soil survey reports. In addition, one can use nomographs (Wischmeier and Smith, 1978) or tables based on soil characteristics (Stewart et al., 1975) to estimate values for a particular soil texture. Therefore, there is knowledge uncertainty in the fact that we do not know which value is appropriate for use in our model for the soil type in question. In addition, the erodibility, which is often assumed to be an inherent soil property with a constant value, has been found to vary spatially within a given soil type (Bajracharya and Lal, 1992) as well as temporally (Romkens, 1985).

In our analysis, we defined the variability in annual rainfall erosivity (R) as a temporally stochastic parameter. The soil erodibility (K) and cropping and management (C) factors were treated as having knowledge uncertainty. The LS and P factors were treated as constant, deterministic values under the assumption that the lengths and slopes of the plots were controlled and no support practices were utilized on the plots in question, respectively. The C factor for the fallow plot (1-8) was also assumed to be deterministic and set equal to unity.

Annual rainfall erosivity values were found to be lognormally distributed using 27 years of measured values for the Guthrie plots. The possible ranges of the knowledge uncertain parameters (K and C) were set based on the range of reasonable values found in the literature. A uniform distribution was used initially for both parameters with knowledge uncertainty. We tested the effect of assuming other distributional shapes later in the study. Table 3.2 contains the distributions assigned for the parameters representing stochastic variability and knowledge uncertainty.

The range of possible K factor values was determined from Natural Resource Conservation Service (NRCS) tables and seven additional sources or methods (Stewart et al., 1975; Wischmeier and Smith, 1978; Schwab et al., 1981; Henley et al., 1987; Sharpley and Williams, 1990; Risse et al.,1993; Risse et al., 1994). The resulting range is shown in table 3.2. The cropping and management factor (C) was estimated on an annual basis and the range of possible values was determined from NRCS tables and five additional sources or methods (Beasley, 1972; Stewart et al., 1975; Wischmeier and Smith, 1978; Line and Coffey, 1992; Risse et al., 1993). The resulting range is shown in table 3.2 for each plot.

It is important to include correlations between input distributions during error propagation to ensure realistic results (Reckhow, 1994). A distribution-free rank correlation methodology (Iman and Conover, 1982) is employed by the @Risk software and correlation coefficients ranging from -1 to 1 can be assigned subjectively to dependent variable pairs. We assumed that the correlation between the different factors in the USLE were negligible. We did, however, incorporate correlations later during our discretization analysis.

RESULTS AND DISCUSSION

Two-Phased Monte Carlo Simulation

We applied the two-phased Monte Carlo procedure to the USLE for each of the four Guthrie, Oklahoma plots. The Monte Carlo procedure was performed using 100 simulations (knowledge uncertainty) with each simulation consisting of 1000 iterations (stochastic variability). The sample sizes were determined based on an inspection of figures 3.3a and 3.3b showing the means, 90% confidence intervals, and standard deviations versus number of iterations. These iterations were performed using plot 1-1 parameter estimates. Figure 3.3a shows the results of varying only the parameters with knowledge uncertainty (K and C) and figure 3.3b shows the results of varying only the stochasticly varying parameter (R). In these figures, we looked for the mean and standard deviation to stabilize as well as the confidence intervals to flatten, becoming fairly constant. We assumed that 100 samples for knowledge uncertainty and 1000 for stochastic variability would provide adequate precision and numerical stability for our analysis.

Figure 3.4 shows the distribution of CCDFs of estimated average annual soil loss resulting from 1000 iterations within 100 simulations for plot 1-1. Recall that each individual CCDF represents stochastic variability using a fixed set of knowledge uncertain parameter values and the distribution of CCDFs represents the uncertainty do to lack of knowledge. A less congested summary of this information is presented in figure 3.5, which provides the 5th, 50th, and 95th percentile curves of the distribution of CCDFs. The remainder of the results are presented using this summary technique.

In figure 3.5 we also present the complementary empirical distribution function (EDF) (Conover, 1980) for the 27 years of observed soil loss and the EDF for estimates of soil loss on plot 1-1 conducted by Risse et al. (1993). The Risse et al. (1993) estimates were computed for each year using the observed R values and NRCS estimates of K and C. It is important to note that Risse et al. (1993) did not present their estimates as distributions, but rather as estimates for given years to be compared one-to-one with the observed values for that year. Also shown (fig. 3.5) are the observed mean annual soil loss value and a deterministic USLE estimate using R as estimated from an isoerodent map (Wischmeier and Smith, 1978) and K and C values from NRCS tables for Oklahoma.

A visual comparison of the observed EDF of soil loss and our stochastic estimates with 90% confidence intervals indicated that we consistently over-predicted soil loss on this plot (fig. 3.5). The low probability, high soil loss events were the only portion of the observed EDF that fit within our 90% confidence intervals. Our 50th percentile distribution of estimates and those of Risse et al. (1993) were very similar in magnitude as well as distributional shape. Since the observed distribution of soil loss fell outside our confidence intervals, one must conclude that either the standard methods for estimating the input parameters or the model itself is inadequate and reject the hypothesis that the model-parameter estimation procedure combination is capable of estimating soil loss at the 90% confidence interval (Haan et al., 1995).

It is interesting to note that the observed mean and deterministic USLE estimate compared well. Therefore, if one were to merely compare mean observed soil loss with the average soil loss estimate of the deterministic USLE, one would conclude that the model performs well. In addition, the mean observed soil loss fell within our 90% confidence intervals. However, the highest observed soil loss from 1949 (540 Mg/ha) greatly influenced the mean of the observed soil loss.

The CCDF percentiles of estimated soil loss for plot 1-2 are shown in figure 3.6. In this case much of the observed EDF fell within our 90% confidence intervals. However, we over-predicted the lower soil loss portion of the distribution (< 30 Mg/ha) and under-predict the high soil loss portions (> 150 Mg/ha). Again, the observed mean and USLE deterministic estimate compared favorably. Note that the mean observed annual soil loss did not fall within our 90% confidence interval even though our soil loss distribution estimate was much closer than the observed EDF than it was for plot 1-1.

Simulated CCDFs for plot 1-3 showed that we again consistently over-predicted annual soil loss (fig. 3.7). It is interesting to note that the first three plots (1-1, 1-2, 1-3) had the same cropping and management practices, soil type, and slope. The only difference was the length of slope. We used deterministic estimates of the LS factor under the assumption that little variability would be present and that there was basically only one possible estimate for each plot. However, the fact that we were able to predict soil loss from plot 1-2 with some success, but not from the two plots with shorter lengths, suggests that there was some unexplained variability between plots or that model error in terms of the slope length is significant.

The resulting annual soil loss distribution estimates and observed data for plot 1-8, the fallow plot, are shown in figure 3.8. Again, we greatly over-predicted the soil loss distribution. In fact, for the first time, the USLE deterministic value was not a good estimate of the mean observed annual soil loss. Risse et al. (1994) discussed the fact that this fallow plot was different from the standard fallow plots since it was not plowed and became highly consolidated. This may explain our inability to simulate the annual soil loss distribution, but further analysis was beyond the scope of this study.

With the exception of plot 1-2, the estimated soil loss distributions using the USLE greatly over-predicted the observed soil loss distributions from the Guthrie, Oklahoma plots. However, a comparison of the mean observed soil loss and a standard deterministic estimate with the USLE would suggest otherwise. The EDFs of observed soil loss were highly skewed with many small annual values and a few very extreme outliers. The USLE was developed as an estimate of "average" annual soil loss and it does appear to do a good job of estimating this "average" or mean value. However, this average value would tend to produce overly conservative estimates and does not provide adequate information for decision making. If one wants to be conservative in their decision making process they should know the degree of conservatism in calculations and decisions (Hattis and Burmaster, 1994). A stochastic representation of the annual soil loss as provided by a quantitative uncertainty analysis allows for more useful information for planning and management (Finkel, 1994). Given a CCDF of soil loss, decisions on the level of management could be made based on probability of occurrence and the level of risk acceptable to resource managers.

Effects of Parameter Probability Distribution Assumptions

In order to perform a quantitative uncertainty analysis in a H/WQ model, probability distributions must be assigned to each of the uncertain model parameters. In some cases, observed data may be available for the analyst to adequately evaluate the underlying distribution. For example, in this study we were able to fit 27 years of rainfall erosivity estimates to a lognormal distribution. However, information concerning parameter uncertainty is seldom available, even for a portion of the parameters in a model (Gardner and O'Neill, 1983). Therefore, approximations must be made based on the best available information or subjective judgement.

When subjectively defining input parameter distributions, Hammonds et al. (1994) suggested the use of uniform or triangular distributions when the range of values is less than a factor of 10. If the range of possible values exceeds a factor of 10, they preferred to assume a probability distribution of the logarithms of the parameter values, resulting in either log-uniform or log-triangular distributions. In deciding between a uniform or triangular distribution, Hammonds et al. (1994) suggested the uniform distribution where data are limited or based on purely literature values, and the triangular distribution if there is prior knowledge about a most likely value or midpoint based on site-specific information. Though we could have used triangular distributions in our study since actual parameter estimates were made using data from the Guthrie plots, we utilized uniform distributions for K and C in order to reflect the uncertainty in the USLE under normal application.

We simulated the annual soil loss from plot 1-1 using several different distributional shapes for the knowledge uncertain parameters (K and C). We set the rainfall erosivity parameter (R) equal to the median observed value and varied only K and C for 100 simulations. Figure 3.9 displays the annual soil loss output distribution results obtained by assigning uniform, triangular, normal, and lognormal distributional shapes to the knowledge uncertain parameters, K and C. The triangular distributions were set using the same range as those assigned for the uniform distribution (see table 3.2) with a mode equal to the center of the range. The normal and lognormal distributions were then defined with means equal to the mode of the triangular distribution and variances equivalent to those computed for the triangular distributions.

The output distributions illustrated in figure 3.9 showed that the use of triangular, normal, and lognormal probability distributions resulted in very similar soil loss CCDFs. However, use of the uniform distribution for input parameter uncertainty resulted in greater uncertainty as indicated by a lower slope and a wider range exhibited by the CCDF. It is important to note that the variance of the uniform distributions were higher than those of the other three distributions. Therefore, it appears that the variance of the parameter distribution, not the shape, is the most important aspect when subjectively defining parameter distributions.

Use of subjectively determined triangular distributions rather than assuming a normal or lognormal distribution had little effect on output distributions. Rather than spending valuable time and resources on defining complex probability distributions, the use of a triangular distribution based on probable ranges of input variables appears to be adequate for propagation of uncertainty. In addition, the use of the uniform distribution to express greater uncertainty in parameter estimation procedures resulted in greater output uncertainty as expected. More comprehensive research is needed to validate these findings using various H/WQ models in a distributed parameter context and for alternative distributional assumptions.

Effects of Discretization on Uncertainty Propagation

Most H/WQ models are distributed-parameter models to some extent. These models rely on discretization of a watershed into smaller units that are then assumed to be homogeneous in terms of input parameters and mathematical representation. To test the effect that discretization has on model output variance as propagated using Monte Carlo techniques, we simulated plot 1-1 at different levels of discretization as illustrated in figures 3.10a through 3.10e. We divided the plot vertically so as not to affect the slope length factor.

We estimated the annual soil loss for each discretization level in figures 3.10a through 3.10e by computing the soil loss from each sub-unit as a mass per unit area (kg/ha) using the USLE, multiplying these by the area of the sub-unit to get a mass (kg), and adding these soil losses for the sub-units together resulting in an annual soil loss estimate for the entire plot in kg. We varied the K and C factors for 100 iterations for each sub-unit using LHS sampling. It is important to note that the K and C values for each sub-unit were sampled independently.

Correlations between different parameters in the USLE were assumed to be negligible throughout the previous analyses. However, correlations in the same parameter, across different sub-units are probably not insignificant. In particular, in this investigation we merely discretized a small, relatively homogeneous plot and the correlation of a single parameter from one sub-unit to the next is probably very high. However, when modeling entire watersheds at a variety of discretization levels, we do not know the actual correlation structure of the natural system. To investigate the combined effect of discretization level and parameter correlation on output variance, we simulated annual soil loss for five different discretization levels (fig. 3.10a through 3.10e) and five levels of correlation (0.0, 0.25, 0.50, 0.75, and 1.0). The correlations were accounted for within @Risk using a distribution-free rank order methodology.

The results of our investigation into the combined effects of discretization level and parameter correlation on output variance are shown in figure 3.11. Assuming no parameter correlations from sub-unit to sub-unit, the output variance was reduced significantly merely by the act of discretization. One might argue that the uncertainty should be reduced when modeling an area as more detailed, homogeneous units. However, we did not reduce the range of our parameter estimates to reflect this reduction in knowledge or spatial uncertainty. Therefore, the reduction in output uncertainty was purely of a mathematical nature, not related to the knowledge of the model user. We argue that a more detailed discretization of a watershed or other area under study should result in less uncertainty in the parameter estimates (reflected by a lower range or more centrally-based distribution type) which would then result in a reduction in output uncertainty.

Mathematically, this reduction in output variance due to discretization can be illustrated through inspection of the underlying statistics. As an example, we examined the case where the parameter correlations between sub-units were set to zero. The total annual soil loss from a discretized plot is a linear function of independent random soil loss estimates from the sub-units:

$$Z = \sum_{i=1}^{m} a_i \, x_i \tag{3.2}$$

where Z is the annual soil loss estimate for the entire plot (kg), a_i is the area of the i^{th} sub-unit (ha), x_i is the annual soil loss per unit area of the i^{th} sub-unit (kg/ha), and m is the number of sub-units. The variance is defined as (Devore, 1987):

$$Var(Z) = \sum_{i=1}^{m} a_i^2 \; Var(x_i) \tag{3.3}$$

where $Var(Z)$ is the variance of annual soil loss for the entire plot (kg^2). Note that since the variables are independent and random, the covariances are equal to zero. Since the sub-units are equal in size, the areas of the i^{th} sub-units can be redefined as:

$$a_i = \frac{A}{m} \tag{3.4}$$

where A is the area of the entire plot (ha). Therefore, the variance of Z becomes:

$$Var(Z) = \sum_{i=1}^{m} \frac{A^2}{m^2} \; Var(x_i) \tag{3.5}$$

Furthermore, for the simulations discussed above, the variances of the x_i's were approximately the same since we did not adjust the distributions of the input parameters (K and C) and the USLE estimates of soil loss per unit area were nearly equivalent. Therefore, the variance of Z becomes:

$$Var(Z) = \frac{A^2}{m^2} \ m \ Var(x_i) = \frac{A^2}{m} \ Var(x_i) \tag{3.6}$$

This mathematical evaluation matches our simulation results shown in figure 3.11 as the line representing the change in variance assuming no correlations. For example, the variance of the soil loss estimate for the plot with five sub-units (fig. 3.10e), where m = 5, had a variance approximately 1/5th that of the undivided plot, where m = 1.

It is important to note that we have made some simplifications and assumptions to illustrate our point. For instance, the x_i's for our discretized plots were nearly equal since we did not change the input distributions. When simulating a watershed or other heterogeneous system, one would most likely change the input estimates for each discretized area to reflect this heterogeneity. However, the inputs and their variances will likely not change significantly from discretization to discretization and the reduction in variance would still occur purely for mathematical reasons. In addition, in the derivation above, we assumed no correlations from variable to variable or for the same variables across discretizations. However, the results shown in figure 3.11 illustrate that, unless we assume correlations equal to 1.0 across discretizations, the mere act of discretization results in a reduction in output variance.

Many distributed parameter models require the discretization of watersheds into uniform grids. This can result in thousands of discrete sub-units used to represent a single watershed. Based on the trend seen in the line representing zero correlations, we could expect the output variance to be nearly equal to zero if we sub-divide an area into thousands of discrete units. Does this mean that by simply sub-dividing a watershed into many smaller units we can model the hydrology or water quality with near certainty? In fact, when sub-dividing a watershed we are forced to estimate many more parameters, each with uncertainty, which could actually result in an increase in uncertainty (Suter et al., 1987).

Increased correlations tend to mask the effect of discretization level on output variance (fig. 3.11). Is it therefore possible to conduct Monte Carlo procedures on distributed parameter models and still maintain some control on the output variance? What level of correlation is appropriate? Should this correlation be based on the actual spatial correlation structure in the physical world or can we estimate these subjectively? Morgan and Henrion (1992) suggested that assessing correlation by subjective judgment is difficult to do at best. However, little experimental data exists concerning the correlation structures within watersheds (Sharma and Rogowski, 1985). This is further complicated because the spatial and temporal relationships are site-specific, scale dependent, and vary with the property being measured (Warwick and Nielsen, 1980; Peck, 1983; Parkin, 1993).

Additional research is needed to determine the appropriate level of correlation at the watershed scale for the various parameters used in H/WQ models. In addition, a method of correcting for the mathematical reduction in output due merely to discretization level needs to be developed so that model results can be presented realistically and honestly.

SUMMARY AND CONCLUSIONS

We have proposed a two-phased Monte Carlo methodology that provides for the evaluation and propagation of natural stochastic variability and knowledge uncertainty separately in H/WQ modeling efforts. We illustrated our uncertainty propagation procedures using the USLE and 27 years of rainfall and erosion data from four experimental plots in Oklahoma. Comparisons between our probabilistic estimates of annual soil loss and observed soil loss were made. We concluded that a stochastic representation of annual soil loss is more appropriate for decision making than a conservative estimate (based on a single estimate of the mean that is strongly influenced by extreme values) and allows for management based on the level of risk acceptable to resource managers.

We also showed that the use of subjectively determined triangular distributions, rather than assuming a normal or lognormal distribution, had little effect on output distributions. The use of the uniform distribution to express greater uncertainty in parameter estimates resulted in greater output uncertainty as desired. We also illustrated that output variance was reduced significantly merely by the act of discretization due to the mathematics of the underlying statistics. This is a potential problem since most distributed parameter models discretize the watershed into many uniform units resulting in hundreds or even thousands of discrete sub-units used to represent a single watershed, thereby, greatly reducing output variance. Additional work is needed to test procedures to correct for this false reduction in output variance in order to honestly present output variability and uncertainty for distributed H/WQ models.

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Table 3.1. Guthrie, Oklahoma erosion plot characteristics.

Plot	Size (m) (width by length)	Slope %	Tillage	Crop Type
1-1	1.83 by 11.06	7.7	U/D*	Cotton
1-2	1.83 by 44.26	7.7	U/D	Cotton
1-3	1.83 by 22.13	7.7	U/D	Cotton
1-8	1.83 by 22.13	7.7	U/D	Fallow

* Up and down slope turnplow.

Table 3.2 Parameter distributions and ranges for USLE uncertainty analysis in metric units.

Plot	R	K	LS	C	P
1-1	LN(383,0.67)*	U(0.21,0.45)†	0.57	U(0.42,0.59)	1.0
1-2	LN(383,0.67)	U(0.21,0.45)	1.13	U(0.42,0.59)	1.0
1-3	LN(383,0.67)	U(0.21,0.45)	0.80	U(0.42,0.59)	1.0
1-8	LN(383,0.67)	U(0.21,0.45)	0.80	1.0	1.0

* Lognormal distribution (Mean, Coefficient of Variation).

† Uniform distribution (Minimum, Maximum).

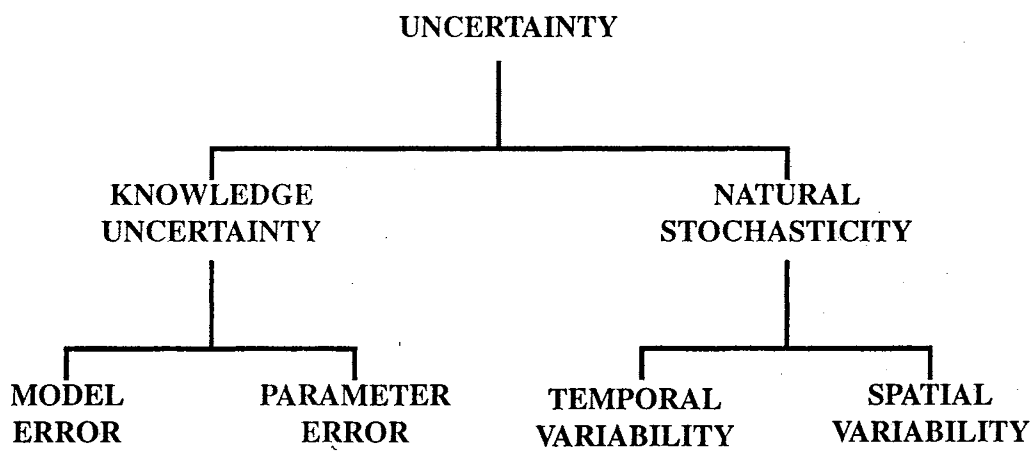

Figure 3.1 Uncertainty taxonomy used in this study.

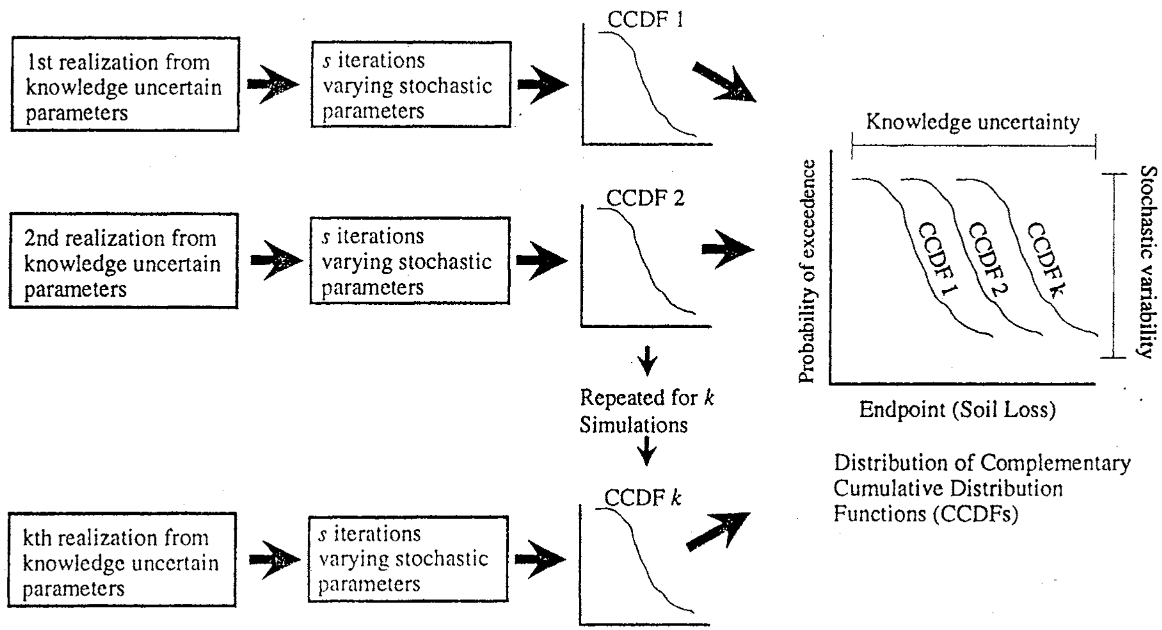

Figure 3.2 Illustration of two-phased Monte Carlo procedure utilized to propagate knowledge uncertainty and stochastic variability separately.

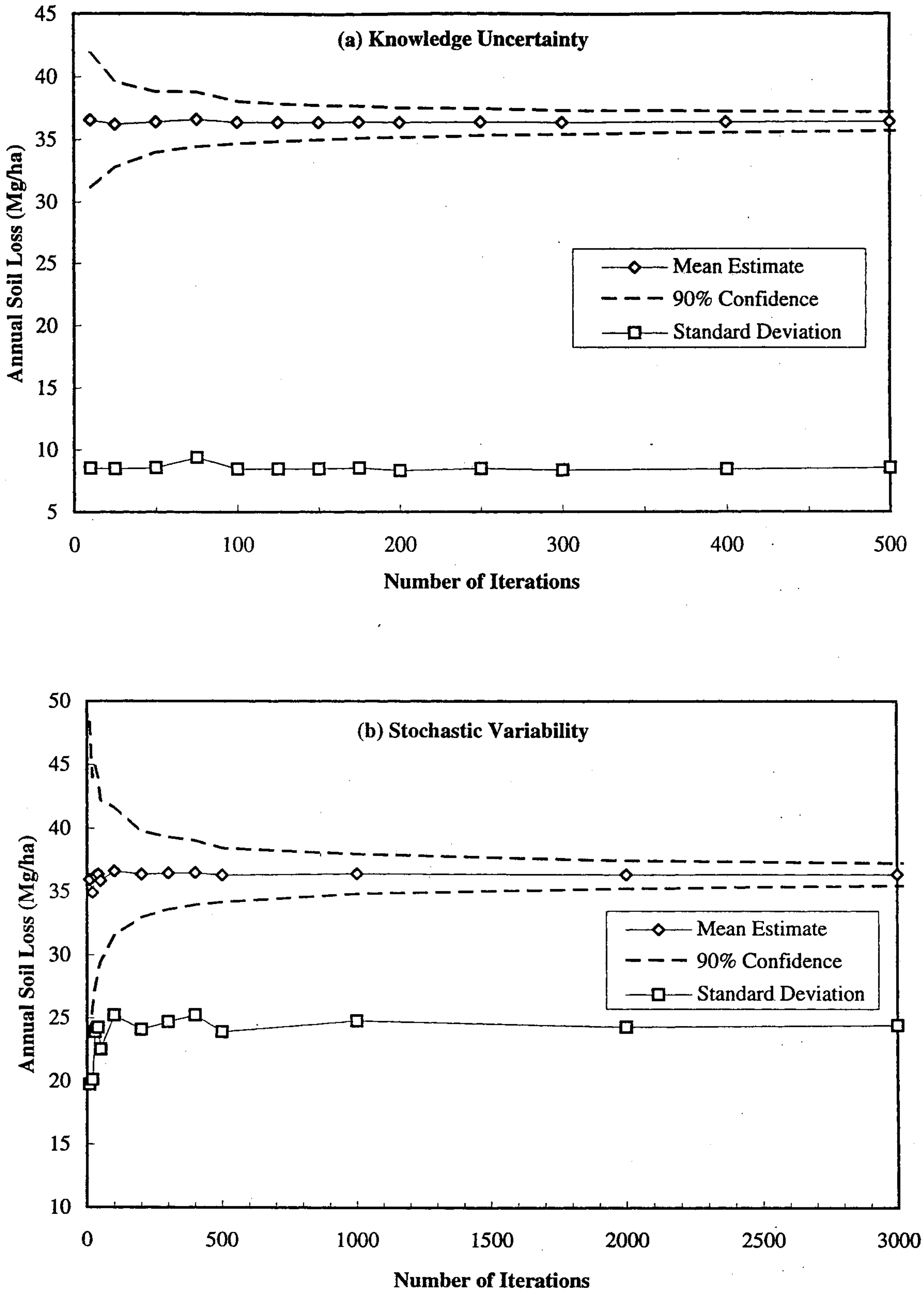

Figure 3.3 Precision determination curves.

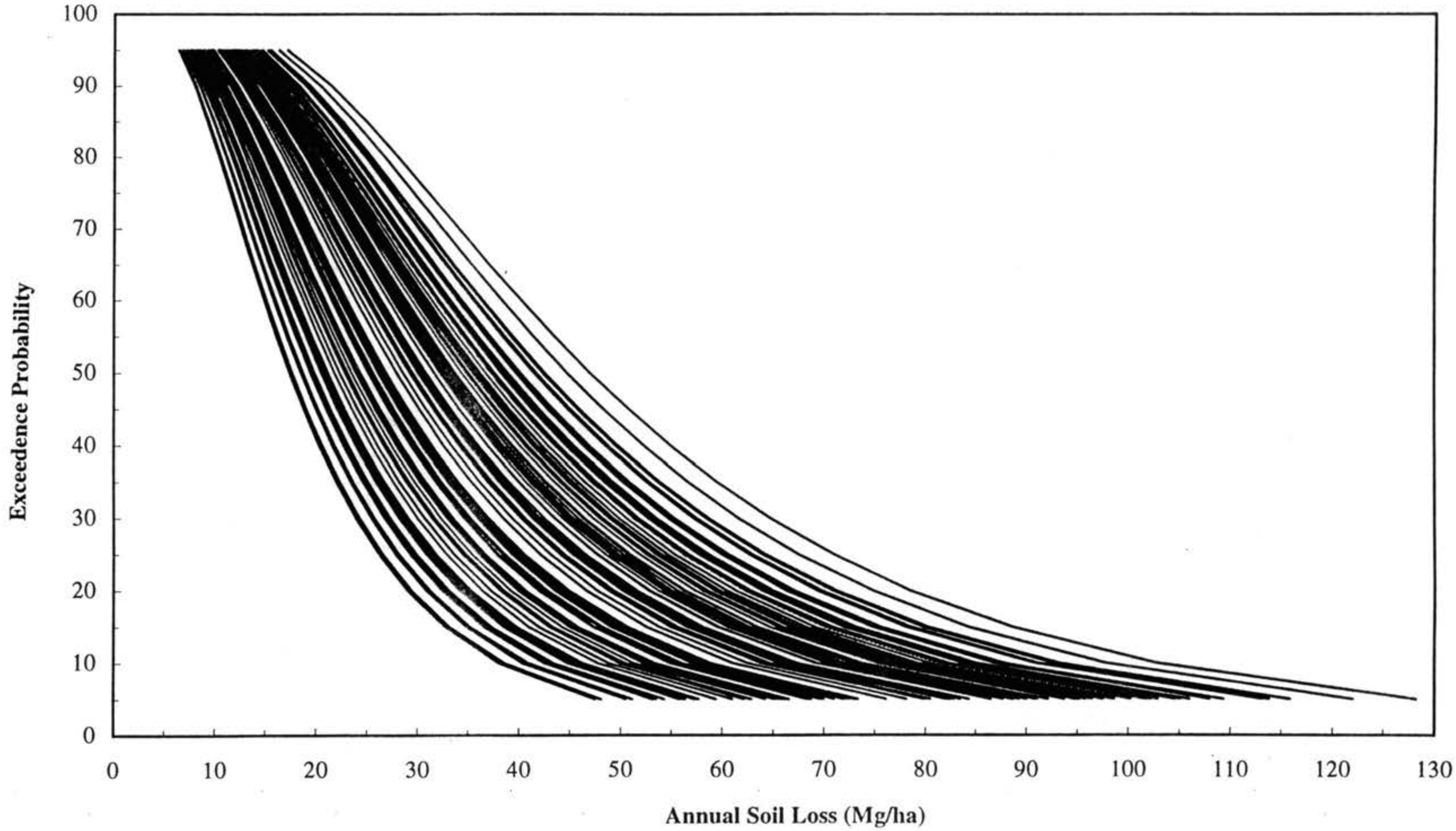

Figure 3.4 Distribution of complementary cumulative distribution functions (CCDFs) of annual soil loss estimates for Guthrie, Oklahoma plot 1-1 using the USLE.

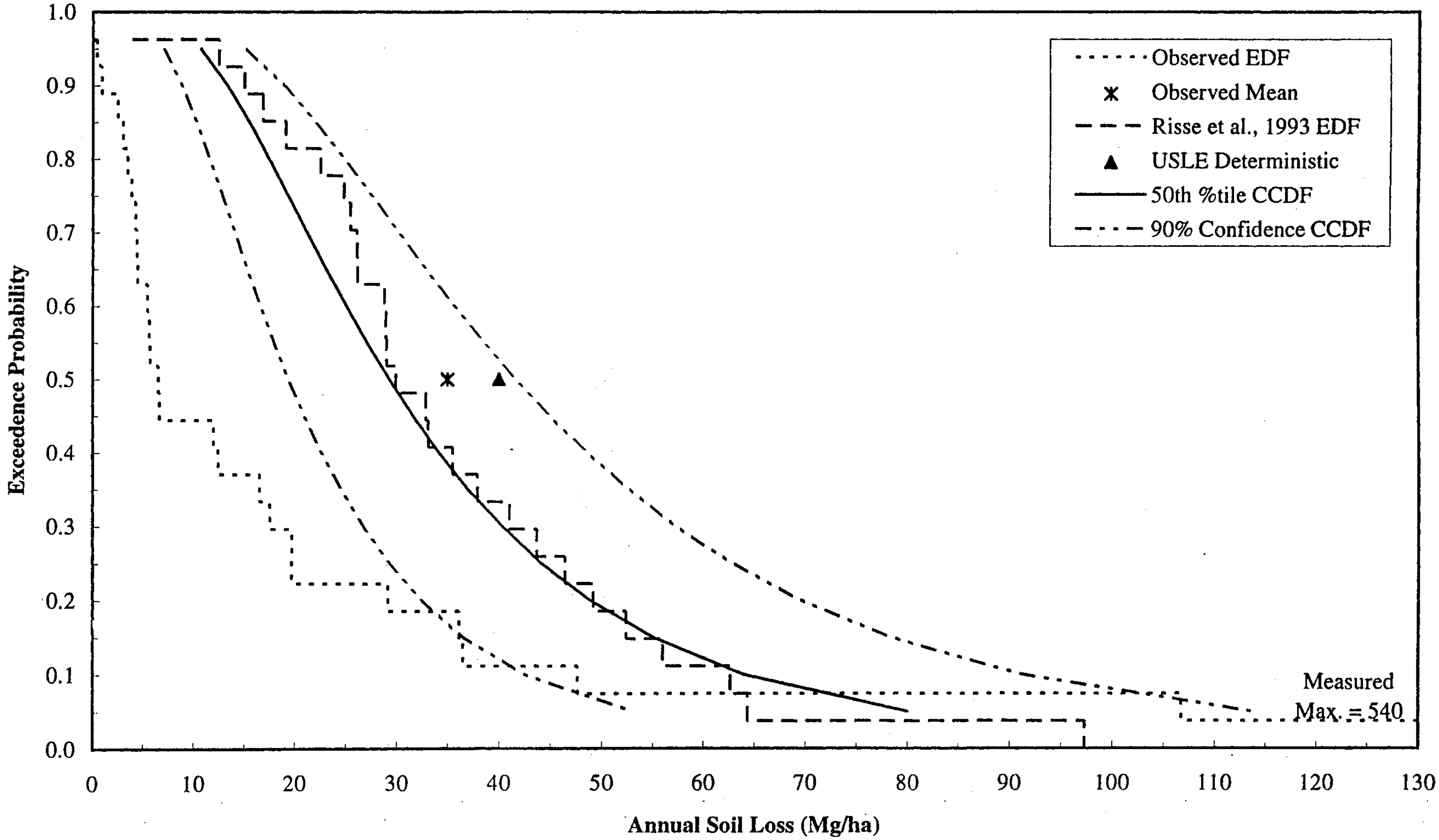

Figure 3.5 Summary of the distribution of CCDFs of annual soil loss estimates for plot 1-1 compared with observed soil loss, previous estimates, and a deterministic USLE estimate.

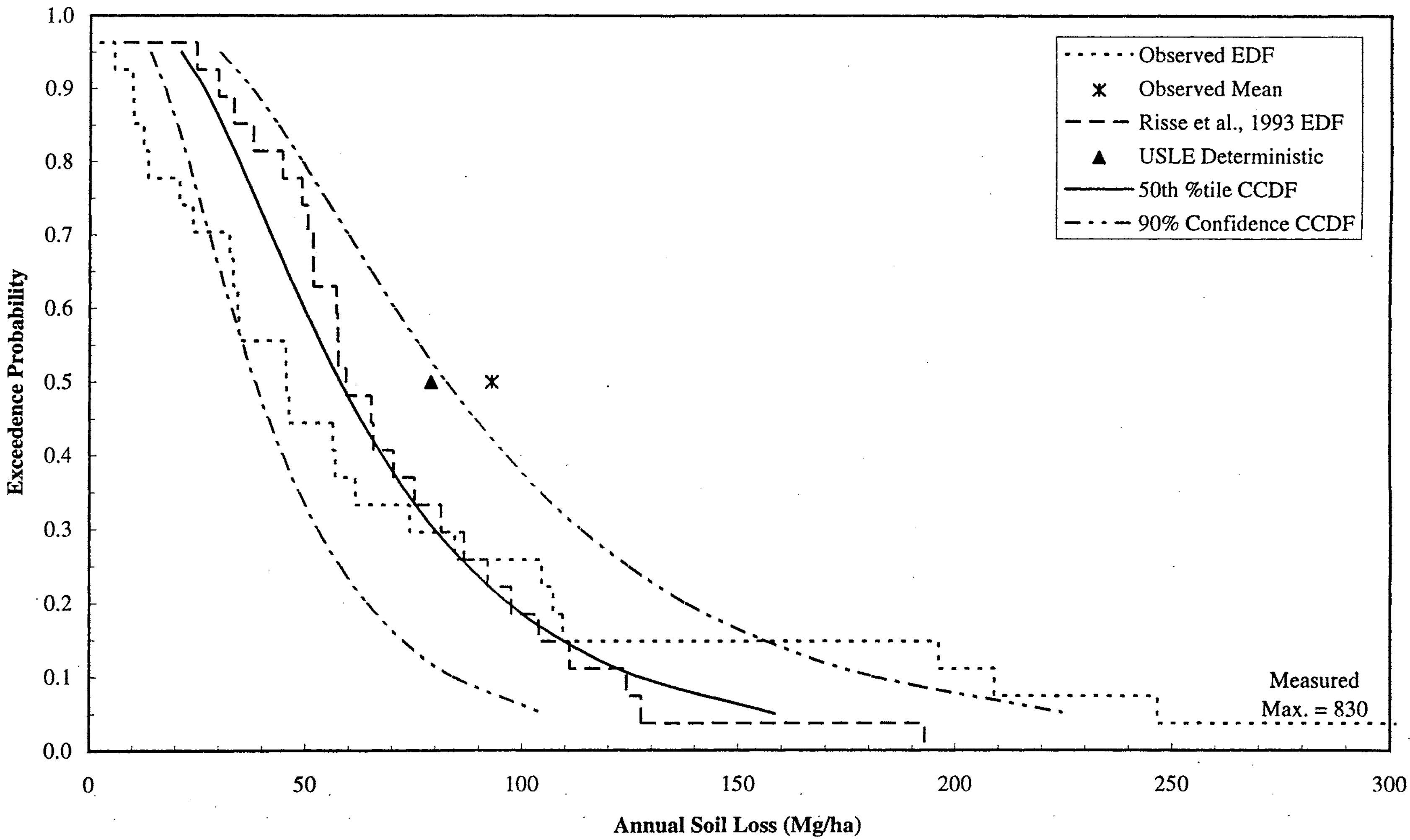

Figure 3.6 Summary of the distribution of CCDFs of annual soil loss estimates for plot 1-2 compared with observed soil loss, previous estimates, and a deterministic USLE estimate.

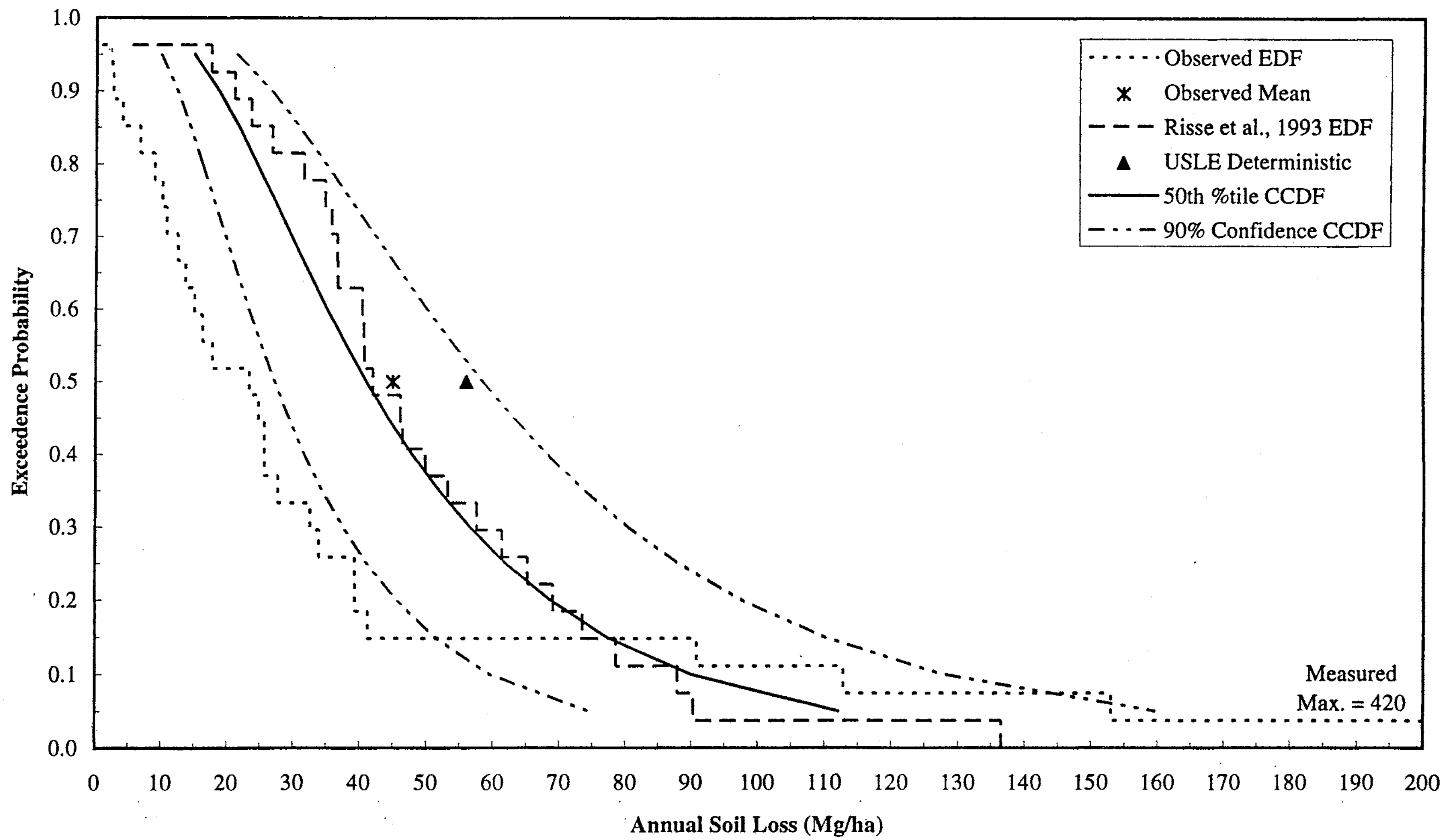

Figure 3.7 Summary of the distribution of CCDFs of annual soil loss estimates for plot 1-3 compared with observed soil loss, previous estimates, and a deterministic USLE estimate.

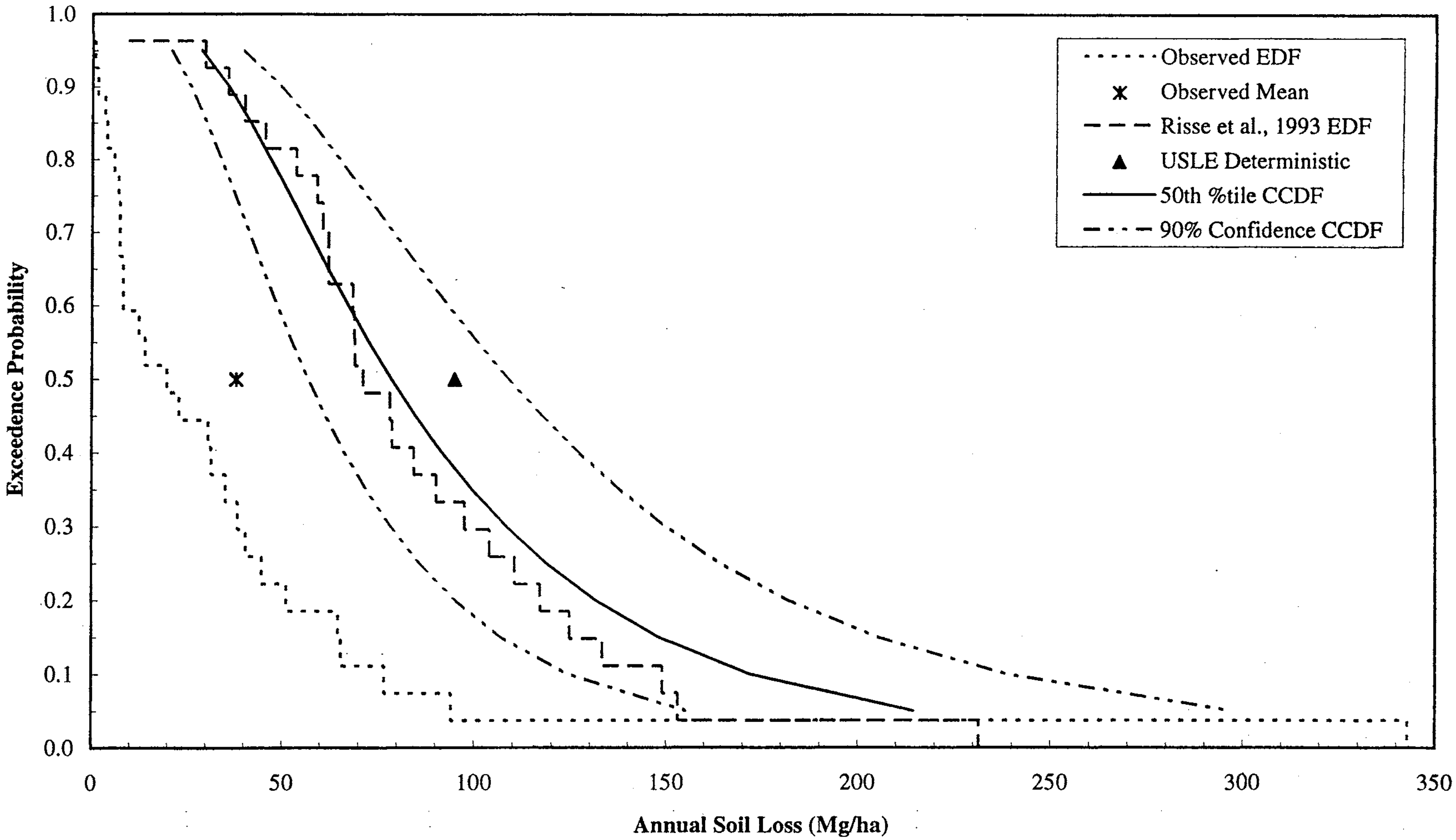

Figure 3.8 Summary of the distribution of CCDFs of annual soil loss estimates for plot 1-8 compared with observed soil loss, previous estimates, and a deterministic USLE estimate.

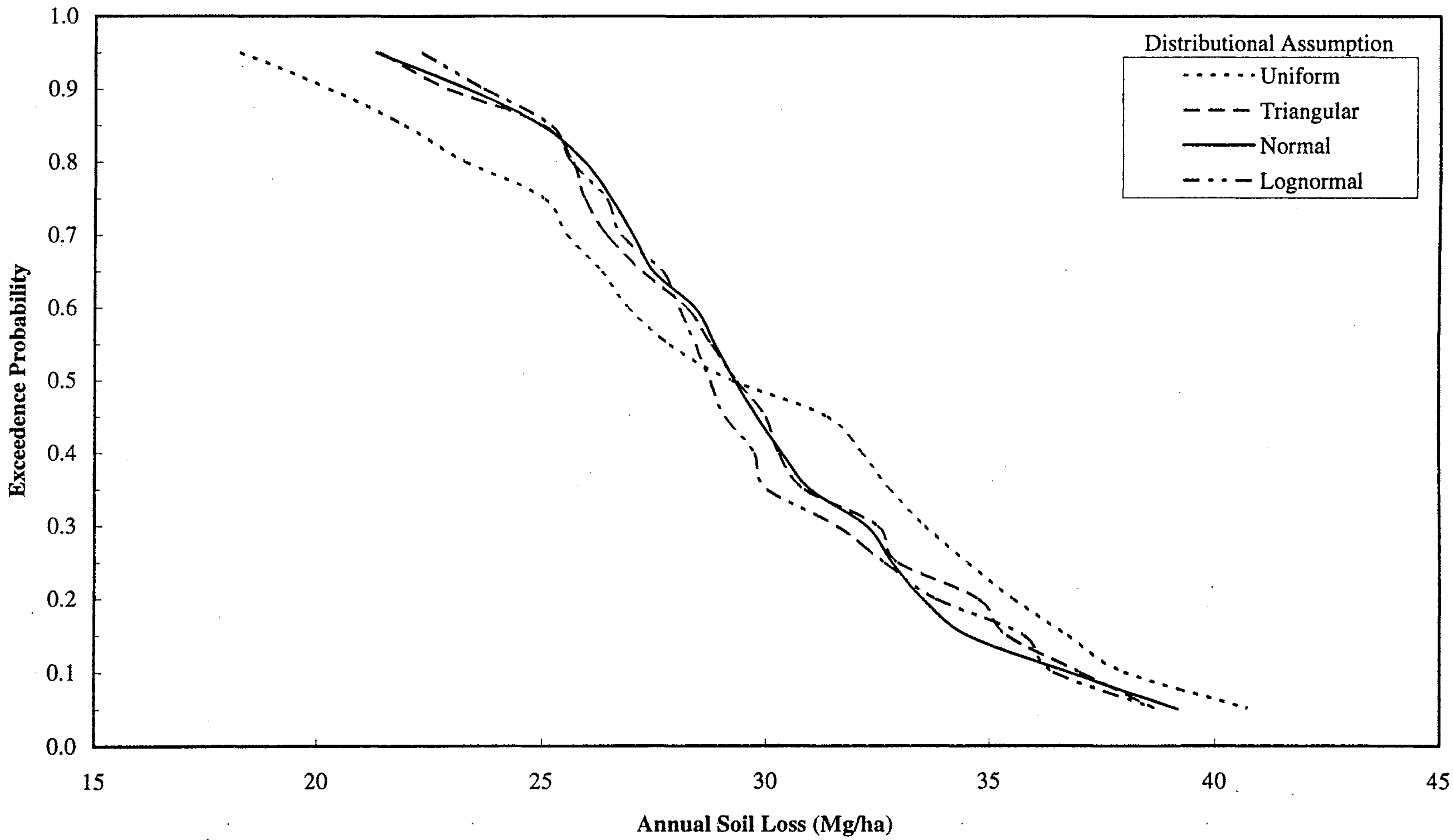

Figure 3.9 Comparison of estimated annual soil loss distributions for plot 1-1 due to four different input parameter distributional shape assumptions for the parameters having knowledge uncertainty (K and C).

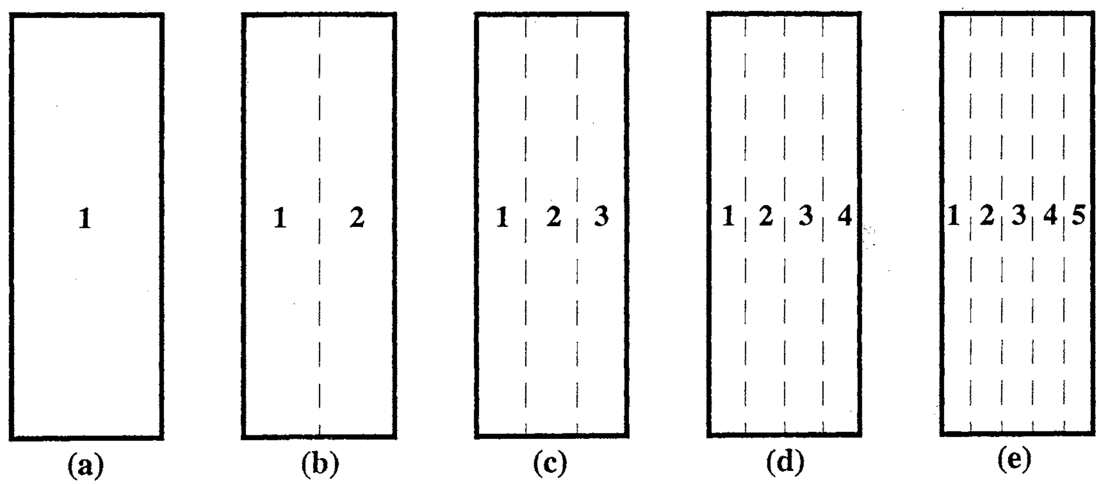

Figure 3.10 Schematic of five discretization levels utilized to test the effects of discretization level on output variance.

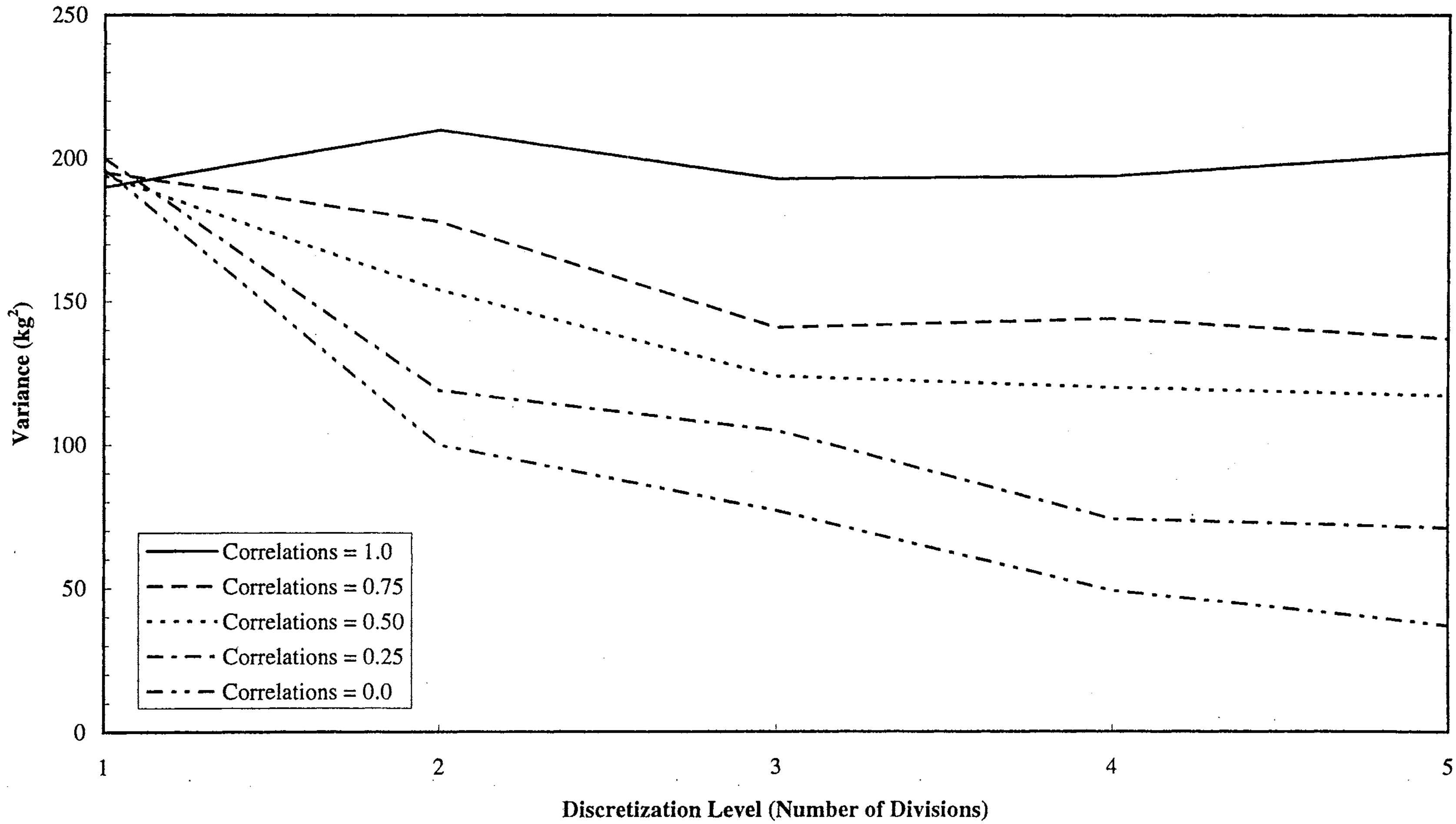

Figure 3.11 Relationship between estimated annual soil loss variance and level of discretization for five levels of parameter correlation.

CHAPTER 4

A WATERSHED-LEVEL ECOLOGICAL RISK ASSESSMENT METHODOLOGY

ABSTRACT. *We present an ecological risk assessment methodology at the watershed level for freshwater ecosystems. The major component is a pollutant transport and fate model (a modified EUTROMOD) with an integrated uncertainty analysis utilizing a two-phased Monte Carlo procedure. The uncertainty analysis methodology distinguishes between knowledge uncertainty and stochastic variability. The model assesses the ecological risk of lentic ecosystems in response to the stress of excess phosphorus resulting in eutrophication. The methodology and model were tested on the Wister Lake watershed in Oklahoma with the lake and its trophic state as the endpoint for ecological risk assessment. A geographic information system was used to store, manage, and manipulate spatially referenced data for model input.*

INTRODUCTION

Ecological risk assessment (Suter 1990; Cairns and McCormick 1991; Risk Assessment Forum 1992; Lipton et al. 1993; Suter 1993; Matlock et al. 1994) and watershed-level management (U.S. EPA 1991; Browner 1993; Doppelt et al. 1993, Perciasepe 1994) are quickly becoming fundamental components of environmental decision making concerning the Nation's water bodies. Appropriate tools and methodologies are needed to allow for ecological risk assessment and watershed management while addressing uncertainties in knowledge, data, and ultimately, predictions. The tools and methodologies should be useful for assessment and decision making for local, state, and federal agencies. Therefore, they must be user friendly and simple, while providing reliable information with quantifiable uncertainty.

Suter (1993) defined ecological risk assessment as the process of assigning magnitudes and probabilities to the adverse effects of human activities or natural catastrophes. Ecological risk assessments provide a holistic method for analyzing and predicting ecosystem response to stress. However, resource planning and decision-making using ecosystem response can be difficult due to lack of knowledge, intricacies of ecosystem function, and minimal data availability. Therefore, simulation models are often used for analyzing and predicting the response of ecosystems to perturbation (Minns 1992). Uncertainty analyses should be a routine part of ecological risk assessments (Risk Assessment Forum 1992). However, few, if any, existing pollutant transport and fate models proposed for use in ecological risk assessments include thorough uncertainty analyses (Reckhow 1994a).

We propose a methodology for performing ecological risk assessments at the watershed level which incorporates thorough uncertainty analysis to allow for appropriate management decisions. As an example, we evaluated the risk of eutrophication in Wister Lake, Oklahoma as a probabilistic description of uncertain phosphorus inputs. Stream loading and lake response were estimated using EUTROMOD, a watershed-level nutrient loading and lake response model (Reckhow et al. 1992). The uncertainty in loadings and lake response due to natural variability and parameter uncertainty were propagated separately throughout the analysis using a two-phased Monte Carlo simulation methodology. Finally, we illustrated the value of the proposed methodology for risk management by simulating alternative management scenarios for achieving water quality goals in Wister Lake.

PROJECT AREA DESCRIPTION

Wister Lake, located in the Arkansas River Basin on the Poteau River in Oklahoma, was constructed by the U.S. Army Corps of Engineers in 1949 to provide flood control, water supply, low flow augmentation, and water conservation. Wister Lake has a surface area of 2,970 ha, a shoreline length of 185 km, a mean depth of 2.3 m, and a maximum depth of 13.4 m at the normal pool elevation of 146 m (Oklahoma Water Resources Board 1990). The lake is the sole water supply for the majority of residents in LeFlore and three adjacent counties. In addition, the lake and related recreational activities are important to the economy of the area.

Wister Lake has been considered eutrophic since it was first surveyed in 1974 by the U.S. EPA (1977) as part of the National Eutrophication Survey. Oklahoma's 1990 Water Quality Assessment Report classified Wister Lake as eutrophic and highly turbid. In addition, the Wister Lake watershed has been targeted in Oklahoma's Section 319 Nonpoint Source Management Plan as well as in its section 303(d) list of TMDL waters.

The watershed draining into Wister Lake covers approximately 260,000 ha with two thirds in Oklahoma and the remainder in Arkansas (Figure 4.1). The lake receives pollutants from a wide variety of both point and nonpoint sources. There are nine major permitted wastewater treatment plants in Wister Lake's watershed. Nonpoint pollution to the lake includes agricultural, forestry, resource exploration and extraction, and urban sources. A potential major source of nutrients in the watershed originates from a large poultry rearing and processing industry in the region. The manure generated from poultry production is generally applied to permanent pasture, thereby, possibly becoming a source of excess phosphorus.

The Wister Lake watershed includes portions of the Ouachita Mountains and the Arkansas Valley ecoregions (Omernik 1987). Land use in the watershed is approximately three fourths forest and one fourth pasture, with small amounts of cropland, urban, and disturbed land. The topography ranges from level flood plains along Fourche Maline Creek and the Poteau River to gently sloping uplands to steep mountainous areas. The relief ranges from Wister Lake's normal pool elevation of 146 m to the 817 m peak of Rich Mountain in Arkansas.

Presently, a cooperative project is underway to prevent further deterioration of water quality in Wister Lake through control of point and nonpoint pollution sources. Monitoring stations have been established throughout the Wister Lake watershed to assist in determining the magnitude of pollutant loading to the lake, distinguishing sources, and tracking the effectiveness of pollution control activities (Hession et al. 1992; Storm et al. 1994). The U.S. Geological Survey and the Oklahoma Conservation Commission have established seven water quality/quantity monitoring stations on the main tributaries flowing to the lake. Samples were collected at six-week intervals for flow, nutrients, sediments, and other constituents of concern. Four of these stations have continuous automatic samplers for stream flow monitoring. In addition, the Oklahoma Water Resources Board has been performing in-lake monitoring as part of an U.S. EPA-funded Clean Lakes Project.

ECOLOGICAL RISK ASSESSMENT

As a comparatively recent discipline, ecological risk assessment methodologies and concepts are subject to debate and change (Lipton et al. 1993). In addition, risk assessment methodologies dealing with ecosystem responses are difficult to standardize due to the wide variability in the types of ecosystems, intended scopes, available resources, and endpoint objectives. We used the effects-driven retrospective ecological risk assessment paradigm with ecosystem-level effects as described by Suter (1993) for this project. This type of assessment is appropriate where there are observed effects, unknown exposure, and unknown sources. Wister Lake and its tributaries have already been identified as having water quality problems and, although there are strong suspects for pollutant sources, the amount of exposure and importance and distribution of the sources is unknown. There are four sequential components to this type of ecological risk assessment: hazard definition, hazard measurement and estimation, risk characterization, and risk management (Suter, 1993) (Figure 4.2).

Hazard Definition

The hazard definition component includes defining the motives of the assessment, describing the environment to be assessed, and choosing endpoints (Suter, 1993). As mentioned previously, the overall goal of the Wister Lake project is to improve or prevent further deterioration of water quality in the lake. The goals for this particular assessment were to determine the level of impairment of the lake, determine the major sources of phosphorus, and provide information to state and federal management agencies to allow them to implement effective corrective or protective management actions. We defined the environment being assessed as the entire drainage basin flowing into Wister Lake. The watershed was defined as the ecosystem under stress while the lake was viewed as the integrator responding to inputs from the watershed.

We defined two distinct types of endpoints, assessment and measurement, where the measurement endpoint was a measurable environmental characteristic that was related to the socially valued characteristic chosen as the assessment endpoint (Suter 1990). Our assessment endpoint was the trophic state of the lake while our measurement endpoint was chlorophyll *a* concentration which, in turn, can be related back to trophic state or eutrophication. We utilized two separate methods to relate in-lake chlorophyll *a* to trophic state: 1) a fixed boundary system that is based on best judgement as to the transition between neighboring trophic categories from U.S. EPA's National Eutrophication Survey (Gakstatter et al. 1974) and 2) an open boundary system proposed by Vollenweider (1982) that accounts for the uncertainty in allocating a lake to a given trophic state.

Hazard Measurement & Estimation

One of the main tasks in a retrospective ecological risk assessment is to establish that a relationship exists between a pollutant source and an ecological effect. The source is often unclear and can be defined as that aspect of a pollution that is subject to management and to which the assessor attempts to relate exposure and effects (Suter 1993). For effects-driven assessments, the sources are the hypothesized anthropogenic causes of the observed effect. In this assessment, we hypothesized that specific land use practices in the watershed resulted in excessive phosphorus loading to Wister Lake, thereby, causing accelerated eutrophication. Exposure is the process that links sources with effects, where the effects are the changes in the ecological values specified by the assessment endpoint (eutrophication). We utilized a nutrient loading and lake response model, EUTROMOD, to estimate the annual phosphorus loading from the watershed (exposure) and resulting lake trophic state (effect).

Risk Characterization

The results of an ecological risk assessment should be a probabilistic estimate of the ecological effects resulting from specific levels of stress (Cairns and McCormick 1991). We utilized a two-phased Monte Carlo procedure for estimating the probability distribution of annual phosphorus load to Wister Lake and the response of the lake to the load. We, thereby, characterized the risk of eutrophication in Wister Lake as a probabilistic description of uncertain phosphorus inputs.

Risk Management

Risk management is the process of decision making that attempts to minimize risks without undue harm to other societal values (Suter, 1993). Selection of eutrophication and chlorophyll *a* concentration as assessment endpoints allowed us to focus attention upon the predictive models and uncertainty analyses necessary to support decision making. In reality, the selection of water quality goals and endpoints should reflect public values (Reckhow 1994b). Scientists can assess the feasibility of various scientific measures of eutrophication; for example, they can estimate the uncertainty in the endpoints under consideration. However, the public and elected officials (as representatives of the public) should choose the endpoint based on a meaningful relationship between the endpoint and the use and enjoyment of the lake. We evaluated management alternatives using the model and the two methods of relating in-lake chlorophyll *a* to trophic state to illustrate the value and possibilities this methodology has for management and decision making.

THE EUTROMOD MODEL

Model Description

The EUTROMOD computer model was developed to provide guidance and information for managing eutrophication in lakes and reservoirs (Reckhow et al. 1992). It is a collection of spreadsheet-based nutrient loading and lake response models which may be used to relate water quality goals to allowable nutrient inputs. The model, thereby, provides information concerning the appropriate mix of point source discharges, land use, and land management controls that result in acceptable water quality.

Lake-wide, growing season average conditions in a lake are predicted as a function of annual nutrient loadings. Annual loadings are simulated with a simple, lumped watershed modeling procedure which includes the Rational Equation's runoff coefficient for surface runoff (Chow et al. 1988), the Universal Soil Loss Equation (USLE) for estimating soil loss (Wischmeier and Smith 1978), loading functions for nutrient export from nonpoint sources, and user provided point source information. Lake response is predicted by a "robust" set of nonlinear regression equations from multi-lake regional data sets. These regression equations are used to estimate lake nutrient levels and chlorophyll *a* concentrations.

The EUTROMOD model was converted from a share-ware spreadsheet program to Microsoft Excel Version 5.0 (Microsoft Corporation, Cambridge, MA) for use in this study. We also modified the nutrient loading portion of the model to allow for the simulation of up to 10 separate subwatersheds. Previously, the entire watershed flowing into a lake was modeled as a single basin with all parameters lumped by land use. This modification allows for a level of spatially distributed modeling and provides loading estimates by subwatershed for comparison with data from our monitoring stations.

Currently, EUTROMOD allows for minimal uncertainty analysis by providing estimates of model error and hydrologic variability. The model error is provided in terms of lake response estimates plus or minus one standard deviation, which is associated with the error term of the regression models. Year-to-year variability is addressed by utilizing an annual mean precipitation and coefficient of variation to account for hydrologic variability. This hydrologic variability is propagated by utilizing first-order error analysis (Reckhow and Chapra 1983) and is presented as lake response estimates bounded by 90% confidence limits.

These uncertainty estimates within EUTROMOD are useful; however, for several reasons we felt that a more extensive uncertainty analysis must be employed in order to perform a thorough risk analysis. First, although the model error estimates include some parameter uncertainties (Reckhow et al. 1992), parameter uncertainties are not specifically addressed in a manner that allows for detailed sensitivity analysis. Second, the assumptions required for first-order analysis are most likely violated and, therefore, may be inadequate for uncertainty propagation in EUTROMOD. Therefore, we performed our risk analysis using Monte Carlo techniques rather than utilize the uncertainty estimates currently provided within EUTROMOD.

Model Input

Data required for simulating watershed loadings and lake response include information about climate, watershed characteristics, and lake morphometry (Reckhow et al. 1992). Climate parameters include precipitation and lake evaporation estimates. Several parameters are needed to describe the watershed in terms of land use, soils, and topography. Lake morphometry is described using surface area and mean depth. Model inputs are detailed in Table 4.1. The modified EUTROMOD treats each land use within each simulated subwatershed as a homogeneous unit. Many of the input parameters are required for each land use within each subwatershed. Therefore, the number of input parameters depends on the number of unique land uses and the number of subwatersheds simulated.

The pertinent data layers (land use, soils, water bodies, and topography) were compiled for the Wister Lake watershed within the Geographic Resources Analysis Support System (GRASS) geographic information system (GIS) developed by the U.S. Army Corps of Engineers (U.S. Army 1991). All watershed characteristic parameters were area-weighted by land use within each subwatershed utilizing soil, land use, and topographic digital data layers in the GIS (Hession, 1995).

UNCERTAINTY ANALYSIS

Uncertainty Defined

The American Heritage Dictionary (Morris 1978) defines uncertainty as "the condition of being in doubt." In most water quality modeling activities the only thing we are sure of is that we are "in doubt." Many types of uncertainties have been identified in the literature utilizing various taxonomic breakdowns (Suter et al. 1987; Morgan and Henrion 1992; MacIntosh et al. 1994). We utilized the terminology of MacIntosh et al. (1994) who defined the major types of uncertainty as knowledge uncertainty and stochastic variability. Knowledge uncertainty is due to incomplete understanding or inadequate measurement of system properties and is a property of the analyst. We further partition knowledge uncertainty into model and parameter uncertainty. Stochastic variability is due to unexplained random variability of the natural environment and is a property of the system under study. Stochastic variability can be further divided into temporal and spatial variability. Note that this taxonomy is meant for discussion purposes rather than as a strict categorization of uncertainty types. For a more thorough discussion of uncertainty the reader is referred to Suter et al. (1987), Haan (1989), and Morgan and Henrion (1992).

Propagation of Uncertainty

It is important for uncertainty analysis to distinguish between stochastic variability and knowledge uncertainty (Helton 1994; MacIntosh et al. 1994). Knowledge uncertainty can be improved upon by decreasing the possible range of parameter estimates. This can be accomplished by physically sampling the appropriate phenomena, thereby, improving confidence in parameter estimation. However, stochastic variability is a natural property of the system being studied and must be accounted for, but can not be reduced.

Our uncertainty analysis followed the methodology of Helton (1994) and MacIntosh et al. (1994) which involved a two-phase Monte Carlo sampling structure used to propagate uncertainty while separating knowledge and stochastic uncertainty. The uncertainty analysis was performed using @RISK Version 3.1a (Palisade Corporation, Newfield, NY) linked with Microsoft Excel Version 5.0. All random sampling was performed using Latin hypercube sampling (LHS) to ensure full coverage across the range of each sampled variable (Morgan and Henrion 1992; Burmaster and Anderson

1994; Helton 1994).

We included analysis of parameter knowledge uncertainty and stochastic variability utilizing the two-phased Monte Carlo procedure illustrated in Figure 4.3. The analysis of stochastic variability was nested within knowledge uncertainty. This was done by performing *k* knowledge simulations, with *s* stochastic iterations within each simulation. Each iteration resulted in a single estimate of the output, meanwhile, each simulation scenario resulted in a set of *s* simulated outputs. The *s* stochastic output results were then analyzed statistically resulting in a complementary cumulative distribution function (CCDF). The overall analysis resulted in a distribution of *k* CCDFs. The variation in each CCDF showed the effects of stochastic variability on the model estimates while the distribution of CCDFs represented the effects of knowledge uncertainty. Details of the two-phased Monte Carlo procedure utilized in this study can be found in Helton (1994), MacIntosh et al. (1994), and Hession et al. (1995).

Parameter Uncertainty

Upon investigation, all parameters included as input to EUTROMOD have both knowledge uncertainty and stochastic variability. In addition, stochastic variability of most parameters exists in both the temporal and spatial realm. In our analysis, we defined only the variability in annual weather (precipitation and rainfall erosivity) as temporally stochastic parameters. The remaining parameters were treated as having only knowledge uncertainty. We only included knowledge uncertainty for the 17 parameters found to have a significant effect on output variability from a previously conducted sensitivity analysis (Table 4.2) (Hession 1995).

In order to perform Monte Carlo simulations, a probability distribution defining the range of possible values must be defined for each uncertain parameter. The probability distribution for annual precipitation amounts was determined based on analysis of 30 years of weather data (Hession, 1995). Statistical analyses were performed on the annual precipitation data from five weather stations within the watershed and all were found to fit a lognormal distribution adequately. There was little variation between the fitted lognormal distributions from station to station and a single distribution was selected (Table 4.2). Rainfall erosivity distributions were assumed to be lognormal and to have a coefficient of variation of 0.67, as determined from the analysis of 27 years of rainfall erosivity data from Guthrie, Oklahoma (Daniel et al. 1943; Risse et al. 1994).

The ranges and distributions of the parameters representing knowledge uncertainty were assigned subjectively using a few basic rules. The possible range of each parameter was based on the range of reasonable values found in the literature. The distributions were assumed to be either triangular or uniform. If no site specific data were available for a particular parameter, the uniform distribution was assigned. However, if data were available from previous studies in the Wister Lake watershed or nearby, a triangular distribution was employed with the mode set based on the site-specific data. The resulting distributions are shown in Table 4.2. Details concerning parameter estimates and distributional assignments can be found in Hession (1995).

It is important to account for correlations between input distributions during error propagation to ensure realistic results (Reckhow 1994a). A distribution-free rank correlation methodology is employed by the @Risk software, and correlation coefficients ranging from -1.0 to 1.0 were assigned subjectively to dependent variable pairs (Table 4.2). The correlations among the remaining parameters were assumed to be negligible. Details concerning correlation assignments can be found in Hession (1995).

RESULTS AND DISCUSSION

Risk Characterization

We applied EUTROMOD to the Wister Lake watershed for current conditions. The five subwatersheds shown in Figure 4.1 were simulated separately and seven distinct land uses were identified. The land use types and approximate percentage coverage by subwatershed are given in Table 4.3. The land use areas were considered deterministic (known) values except for those of pasture and manured pasture (Hession 1995).

The two-phased Monte Carlo procedure was performed with 200 simulations (knowledge uncertainty) with each simulation consisting of 50 iterations (stochastic variability). Sample sizes were selected based on the number of iterations required to provide numerical stability of the output distributions (Hession 1995).

The distribution of CCDFs of median in-lake chlorophyll *a* concentrations resulting from 50 iterations within 200 simulations for current conditions is shown in Figure 4.4. Each individual CCDF represents stochastic variability using a fixed set of knowledge uncertain parameter values, and the distribution of CCDFs represents the uncertainty due to lack of knowledge. A less congested summary is presented in Figure 4.5, which provides the percentile curves of the distribution of CCDFs. In addition, we included 1993 observed median in-lake chlorophyll *a* for five sampling stations at different locations on the lake from an ongoing Clean Lakes Project (Oklahoma Water Resources Board, unpublished data). Our simulated chlorophyll *a* ranges compared favorably with the observed values. Although these comparisons were by no means adequate for validation, they did provide some confidence in the simulation process. It is important to remember that the EUTROMOD lake model estimates lake-wide median growing season average conditions. Therefore, it would take many years of measured data, averaged on an annual or seasonal basis to validate the model adequately.

Recall that our assessment endpoint is lake trophic state, or the risk of being eutrophic. Many methods have been proposed in the literature for relating in-lake chlorophyll *a* concentrations to trophic state (Vollenweider 1968, 1982; Dobson et al. 1974; Gakstatter et al. 1974). Herein, we utilized two different methods, Gakstatter et al. (1974) and Vollenweider (1982), in order to illustrate a fixed boundary and open boundary system, respectively. Gakstatter et al. (1974) proposed that an average chlorophyll *a* concentration of 10 μg/l represents the breakpoint (or fixed boundary) between mesotrophic and eutrophic lakes based on data from the U.S. EPA's National Eutrophication Survey. Using the 50th percentile curve (Figure 4.5), we might estimate that there was a greater than 95% chance that the lake is eutrophic. However, based on the 5th and 95th percentile CCDFs, the in-lake chlorophyll *a* could range from less than 9 μg/l to 13 μg/l due to knowledge and stochastic uncertainty resulting in a trophic classification from mesotrophic to highly eutrophic.

A more realistic system, in our view, is an open boundary system such as that proposed by Vollenweider (1982) that recognizes the uncertainties involved in using subjective judgement to allocate lakes to trophic categories. He presents the trophic state categories as probability distributions. Therefore, at a given chlorophyll *a* concentration, a given lake would have different probabilities of being classified as oligotrophic, mesotrophic, or eutrophic. Figure 4.6 was derived from data presented by Vollenweider (1982) in summarizing the results of the Organization for Economic Co-operation and Development's (OECD) Cooperative Program on Eutrophication. This figure can be used to estimate a probabilistic expression for lake trophic state. For example, we have included median chlorophyll *a* estimates from the 5th, 50th, and 95th percentile CCDFs at 0.5 probability of exceedence as vertical lines in Figure 4.6. Using the median from the 50th percentile CCDF we estimated that the lake has a negligible chance of being oligotrophic, a 3% chance of being mesotrophic, a 61% chance of being eutrophic, and a 36% chance of be hypertrophic. Such a probabilistic expression makes it clear that lowering the in-lake chlorophyll *a* concentration to levels at or below 10 μg/l based on U.S. EPA's fixed boundary system does not necessarily ensure that the lake will be mesotrophic. Actually, according to Figure 4.6, at 10 μg/l the lake still has a 64% chance of being eutrophic.

At this point, it is important to note that the fixed boundary system of the U.S. EPA and the open boundary from Vollenweider (1982) result from the analysis of a different set of lakes and observed data. It was not our intent to prove or disprove either method for trophic classification, but rather, to present the alternative methodologies as possibilities for use in ecological risk assessments. Additionally, we presented the open boundary system in an attempt to include the analysis of uncertainty throughout all aspects of our risk assessment.

Risk Management

Phosphorus Loads

The stressor in our ecological risk assessment was defined as total phosphorus loading to the lake. Therefore, we present the annual total phosphorus load estimates as stochastic entities and discuss risk management in terms of the control of phosphorus sources in the watershed. A summary of CCDFs for annual total phosphorus load estimates is provided in Figure 4.7. Our 90% confidence intervals indicated annual loads from below 100 Mg/yr to nearly 400 Mg/yr. This was a large range of possible values, thereby, highlighting the extent of our uncertainty in the estimates as well as the effect of year-to-year variability. Although beyond the scope of this study, an important step in risk management will be to reduce the uncertainty in these estimates through improved parameter estimation, as represented by knowledge uncertainty.

The expected value annual phosphorus load CCDFs for the individual subwatersheds are provided in Figure 4.8. These expected value curves were obtained by running the model with knowledge uncertainty, while holding the stochastic variables (PREC and R) at their mean values. Also shown in Figure 4.8 are annual total phosphorus load estimates by subwatershed based on 2 years of record (Lakshminarayanan 1994). It is important to note that these estimates were based on regression analysis of six-week grab samples for only two years of data and, therefore, are probably not representative of average annual loads as estimated by EUTROMOD. Details concerning the procedures used to estimate annual loads by subwatershed from six-week grab samples can be found in Smolen et al. (1993). The estimated loads from the monitoring stations fell within our 90% confidence intervals for all but the Holson Creek and Fourche Maline Creek subwatersheds. In addition, the rank-order from highest to lowest contributing subwatershed was identical. Therefore, both estimation procedures suggest that management activities should be targeted in the lake side and Poteau River portions of the Wister Lake watershed.

The percentages of total phosphorus load contributions by source for the Wister Lake watershed and within each subwatershed are provided in Table 4.4. As with all results of this risk analysis, these percentages were also uncertain and, consequently, they are provided as 5th, 50th, and 95th percentile estimates due to knowledge uncertainty. Nonpoint sources contributed the majority of the annual phosphorus loads (with a median greater than 90%) and point sources contributed only a small fraction of the annual load. Furthermore, agricultural sources, though accounting for only 25% of the watershed area (Table 4.3), were estimated to contribute nearly 80% of the annual total phosphorus load. It appears that a watershed protection strategy should concentrate on controlling nonpoint pollution sources, especially agricultural, and will require extensive use of agricultural best management practices.

Alternative Management Scenarios

To illustrate the use of our probabilistic estimates of stressor (annual phosphorus load) and endpoints (chlorophyll *a* and trophic state), we evaluated possible management alternatives. Due to the variability and uncertainties involved, there are many options for setting management goals to achieve a desired water quality in Wister Lake.

Our management alternatives focused on control of agricultural loads since they were estimated to be the largest source of phosphorus to Wister Lake (Table 4.3). Figure 4.9 illustrates our approach to determining ways to meet a water quality goal of returning the lake to borderline mesotrophic/eutrophic according to U.S. EPA's trophic classification system (Gakstatter et al. 1974). The resulting in-lake chlorophyll *a* reductions due to percentage reductions in agricultural loads are shown in Figure 4.9. First, the EUTROMOD simulations were performed as deterministic estimates by holding all parameters at their expected value for each 5% increment of agricultural phosphorus load reduction ranging from no reduction to 100% reduction. These deterministic results are presented as the expected value curve in Figure 4.9. Next, 50 EUTROMOD simulations were conducted for each 5% increment of agricultural phosphorus load reduction, varying only the stochastic parameters. The results are shown as the 90% confidence intervals due to stochastic variability (Figure 4.9). Finally, 200 EUTROMOD simulations were conducted for each 5% reduction increment while varying only the parameters representing knowledge uncertainty. The results are presented as the 90% confidence interval representing knowledge uncertainty (Figure 4.9). The wider confidence intervals for knowledge uncertainty indicate that the uncertainty due to lack of knowledge is greater than that due to rainfall stochasticity.

Based on the expected value simulations, we need to reduce annual agricultural loads of total phosphorus to the lake by approximately 33% to achieve our water quality goal; shown as the mesotrophic/eutrophic breakpoint line of 10 μg/l in Figure 4.9. Furthermore, it appears unlikely that an oligotrophic condition can be achieved, which was estimated as 4 μg/l by Gakstatter et al. (1974).

The stochastic and knowledge uncertainty 90% confidence intervals can be used to illustrate how uncertain we are in our assessment as well as to set our management strategy with a pre-determined level of confidence. Based on the stochastic confidence interval, the percentage reduction in agricultural loads required to meet our water quality goal ranged from less than 20% to nearly 50%. Additionally, the range of reductions was from 0% to between 60 and 70% based on the knowledge uncertainty confidence intervals. These confidence intervals can be used to include a conservative component in our management plan with a given level of confidence by choosing the management option that represents 95% confidence due to stochasticity, i.e. 50% reductions in agricultural loads, or a given confidence in knowledge uncertainty. Management decisions often incorporate conservative estimates, typically called a margin of safety; however, if one wants to be conservative in their decision making process they should know the degree of conservatism (Hattis and Burmaster 1994). A stochastic representation, as provided by our risk assessment methodology, allows for useful information for planning and management (Finkel 1994). Given the stochastic results illustrated above, decisions on the level of management can be made based on probability of occurrence and the level of risk acceptable to resource managers.

SUMMARY AND CONCLUSIONS

We presented an ecological risk assessment methodology at the watershed level for freshwater ecosystems. The methodology involves a two-phased Monte Carlo procedure that provides for the evaluation and propagation of natural stochastic variability and knowledge uncertainty separately in a pollutant transport and fate model, EUTROMOD. The model and uncertainty propagation methodology allows for evaluating the risk of eutrophication in lentic ecosystems as a probabilistic description of uncertain phosphorus loadings. The result is a tool that is user friendly and simple, while providing reliable information with quantifiable uncertainty.

As an example, the methodology and model were used to perform an ecological risk assessment on Wister Lake in Oklahoma. The EUTROMOD model was used to estimate annual watershed phosphorus loads from point and nonpoint sources as well as resulting lake response (chlorophyll *a* concentration). The chlorophyll *a* concentrations were then related to trophic state utilizing both a fixed and open boundary system. The open boundary system recognizes the uncertainties involved in using subjective judgement to allocate lakes to trophic categories and allows for more thorough uncertainty analysis. Finally, alternative management scenarios were simulated in order to illustrate the value of our methodology for decision making.

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Table 4.1 Input requirements for EUTROMOD with subwatershed capability.

Type	Parameter		Symbol	Units
Climatic	Precipitation (annual mean)		PREC	cm/yr
	Precipitation (coeficient of variation)		PRECCV	fraction
	Precipitation Nutrients:	Phosphorus	PRECP	mg/l
		Nitrogen	PRECN	mg/l
Watershed	Runoff Coefficient		$RC_{i,j}$	fraction
	USLE Parameters:			
	Rainfall Erosivity		R	MJ-mm/ha-h
	Soil Erodibility		$K_{i,j}$	Mg/ha per unit R
	Topographic Factor		$LS_{i,j}$	ratio
	Cropping Factor		$C_{i,j}$	ratio
	Practice Factor		$P_{i,j}$	ratio
	Area per Land Use		$AREA_{i,j}$	ha
	Phosphorus Loading Factors:			
	Dissolved		$LFPDIS_{i,j}$	mg/l
	Sediment Attached		$LFPSED_{i,j}$	mg/kg
	Phosphorus Enrichment Ratio		ENP_j	ratio
	Nitrogen Loading Factors:			
	Dissolved		$LFNDIS_{i,j}$	mg/l
	Sediment Attached		$LFNSED_{i,j}$	mg/kg
	Nitrogen Enrichment Ratio		ENN_j	ratio
	Trapping Factors		TF_j	ratio
	Septic System Information:			
	Number of People		$SEPNUM_j$	per capita-yr
	Phosphorus Load		$SEPP_j$	kg P/person-yr
	Nitrogen Load		$SEPN_j$	kg N/person-yr
	Phosphorus Soil Retention		$RETP_j$	fraction
	Nitrogen Soil Retention		$RETN_j$	fraction
	Point Source Information:			
	Effluent Flow		PSQ_j	MGD
	Phosphorus Concentration.		PSP_j	mg/l
	Nitrogen Concentration		PSN_j	mg/l
Lake	Surface Area		LAREA	km^2
	Mean Depth		LDEPTH	m
	Lake Evaporation (annual mean)		LEVAP	m/yr

Note: Subscript $_i$ refers to number of land uses and $_j$ refers to number of subwatersheds.

Table 4.2 Distributions for parameters with stochastic variability or knowledge uncertainty.

Type of Uncertainty	Parameter	Distribution	Correlations
Stochastic	PREC	Ln(121,0.25)*	R (0.90)
	R	Ln(520,0.67)	PREC (0.90)
Knowledge	$RC_{forest,j}$†	Triangular(0.10,0.25,0.40)‡	none
	$RC_{mpast,j}$§	Triangular(0.15,0.35,0.45)	none
	$C_{past,j}$	Uniform(0.012,0.043)¶	none
	$LFPDIS_{mpast,j}$	Uniform(1.0,5.0)	none
	$LFPDIS_{past,j}$	Uniform(0.15,0.30)	none
	ENP_j	Triangular(1.2,1.5,3.7)	none
	TF_{PR}#	Triangular(0.78,0.92,0.97)	TF_{all} (0.50)**
	TF_{FM}	Triangular(0.78,0.92,0.97)	TF_{all} (0.50)
	TF_{BF}	Triangular(0.78,0.92,0.97)	TF_{all} (0.50)
	TF_{HC}	Triangular(0.78,0.92,0.97)	TF_{all} (0.50)
	TF_{LS}	Triangular(0.78,0.92,0.97)	TF_{all} (0.50)
	$AREA_{pastm,PR}$	Triangular(870,1450,4800)	$AREA_{all}$ (0.50)
	$AREA_{pastm,FM}$	Triangular(390,660,2160)	$AREA_{all}$ (0.50)
	$AREA_{pastm,BF}$	Triangular(360,600,1960)	$AREA_{all}$ (0.50)
	$AREA_{pastm,HC}$	Triangular(90,150,500)	$AREA_{all}$ (0.50)
	$AREA_{pastm,LS}$	Triangular(1350,2250,7400)	$AREA_{all}$ (0.50)
	LDEPTH	Uniform(1.82,2.59)	none

* Lognormal distribution (arithmetic mean, coefficient of variation).
† A subscript of $_j$ indicates that the parameter does not change across subwatersheds.
‡ Triangular distribution (minimum, mode, maximum).
§ Land use indicators: pastm=manured pasture; past=pasture.
¶ Uniform distribution (minimum, maximum).
\# Subwatershed indicators: PR=Poteau River; FM=Fourche Maline Creek; BF=Black Fork Creek; HC=Holson Creek; LS=Lake Side.
** A subscript of $_{all}$ indicates that the parameter is correlated to this parameters across all land uses or subwatersheds ($_i$ or $_j$, respectively)

Table 4.3 Land use percentages by subwatershed and their percent of the total watershed.

Land Use Categories	Poteau River	Fourche Maline Creek	Black Fork Creek	Holson Creek	Lake Side	Total Watershed
Cropland	0	<1	0	0	<1	<1
Pasture	24-27*	26-28	5-7	4-5	19-27	19-22
Pasture-manured	1-5	1-2	1-3	1-2	3-10	1-4
Forest	70	69	92	95	64	75
Urban/Built-up	1	2	<1	0	1	1
Barren Lands	<1	<1	0	0	1	<1
Water/Wetlands	1	1	<1	0	5	1
Percent of Total	27	27	20	7	19	100

* Percentage ranges for pasture and manured pasture based on minimum and maximum values from distributions in Table 4.2.

Table 4.4 Annual phosphorus loads by source based on uncertain EUTROMOD estimates.

Subwatershed	Percentile Estimate*	Point Sources %	Nonpoint Sources: Agriculture %	Nonpoint Sources: Forest %	Nonpoint Sources: Other** %
Poteau River	5TH	14	66	2	1
	50TH	20	74	3	2
	95TH	28	82	5	3
Fourche Maline Creek	5TH	8	76	3	2
	50TH	10	81	5	4
	95TH	14	85	6	4
Black Fork Creek	5TH	1	78	8	0
	50TH	1	85	14	<1
	95TH	2	90	21	<1
Holson Creek	5TH	0	69	13	0
	50TH	0	78	22	0
	95TH	0	86	30	0
Lake Side	5TH	0	76	1	6
	50TH	0	85	2	12
	95TH	0	92	4	21
Total Watershed	5TH	6	74	3	3
	50TH	9	81	5	5
	95TH	13	86	7	9

* Percentiles based on 200 simulations with knowledge uncertainty only.

** "Other" includes disturbed land, precipitation, septic systems, and urban/built-up land.

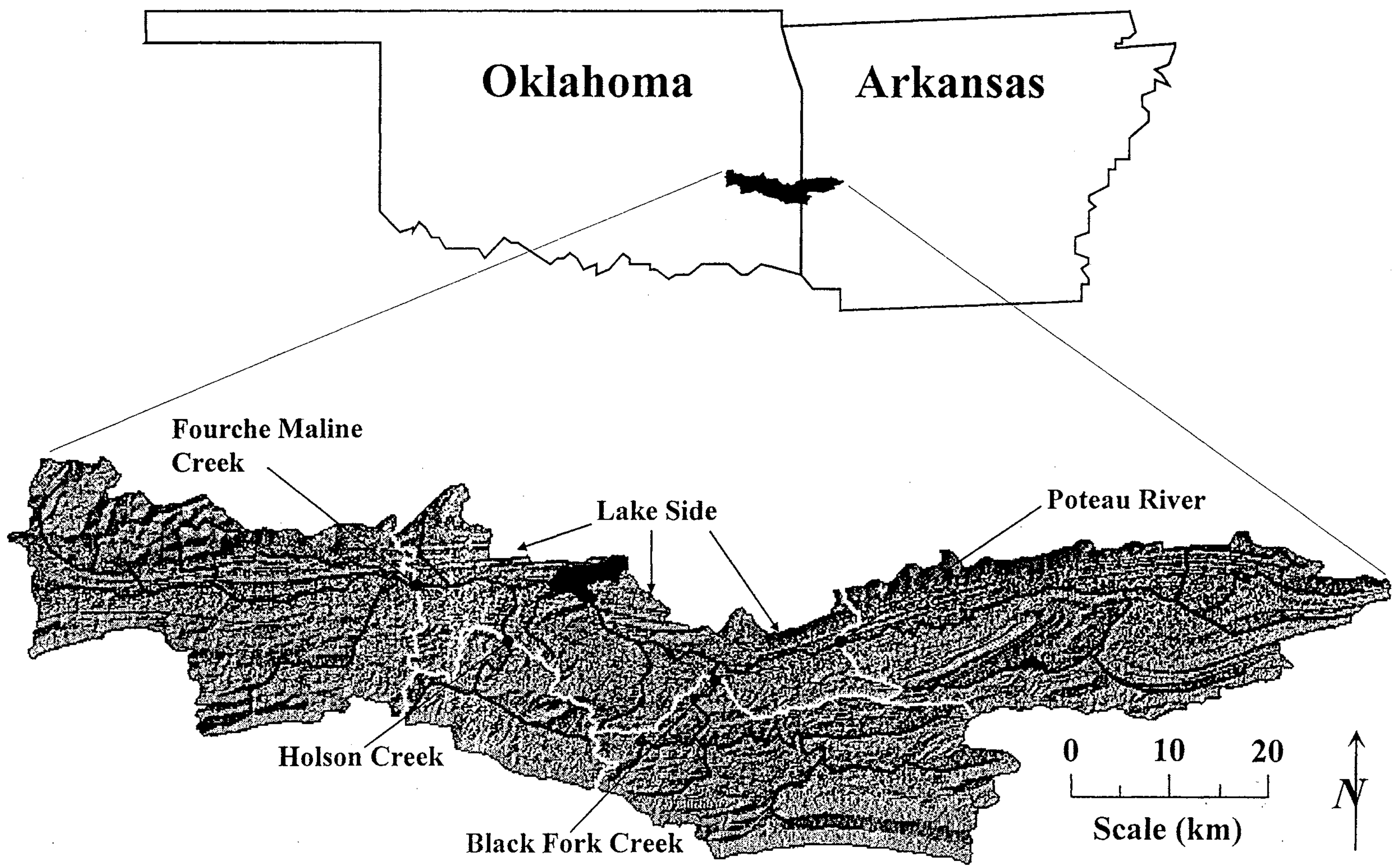

Figure 4.1 Location of the Wister Lake watershed with major subwatersheds identified. Details are shown on an aspect map created from digital elevation data in order to highlight topographic features.

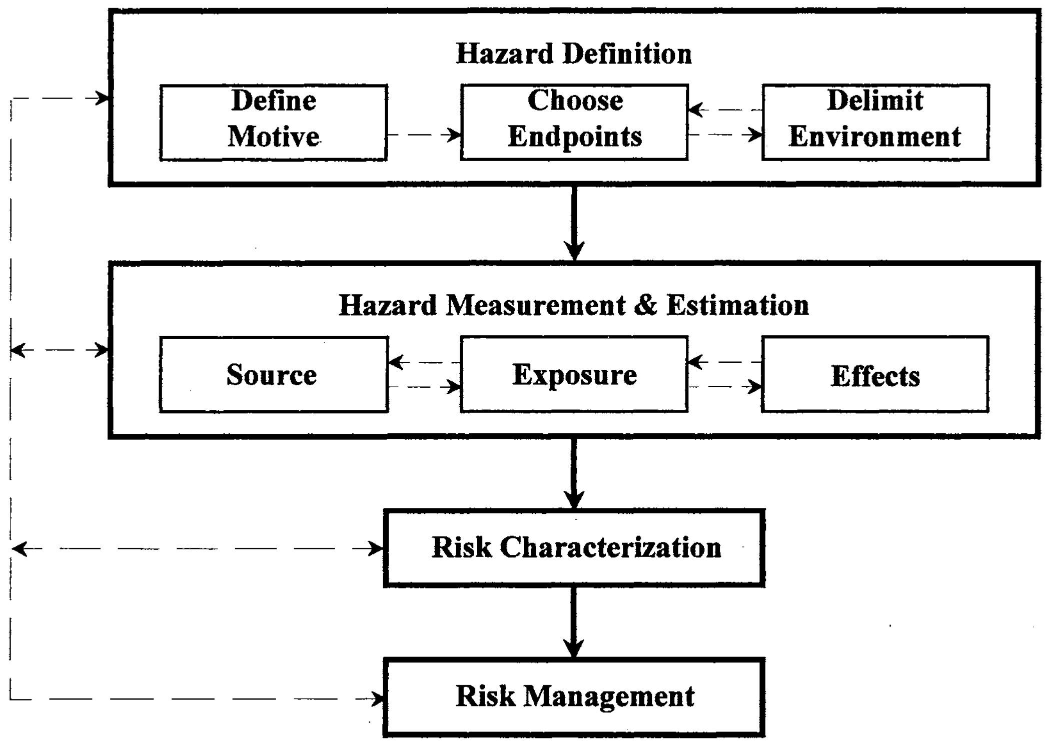

Figure 4.2 Illustration of the retrospective ecological risk assessment paradigm proposed by Suter (1993). The dashed arrows indicate constraints (e.g. the choice of measures of source and effects limits the choice of exposure, and the risk manager's desires constrain all other choices). The solid lines indicate procedural steps.

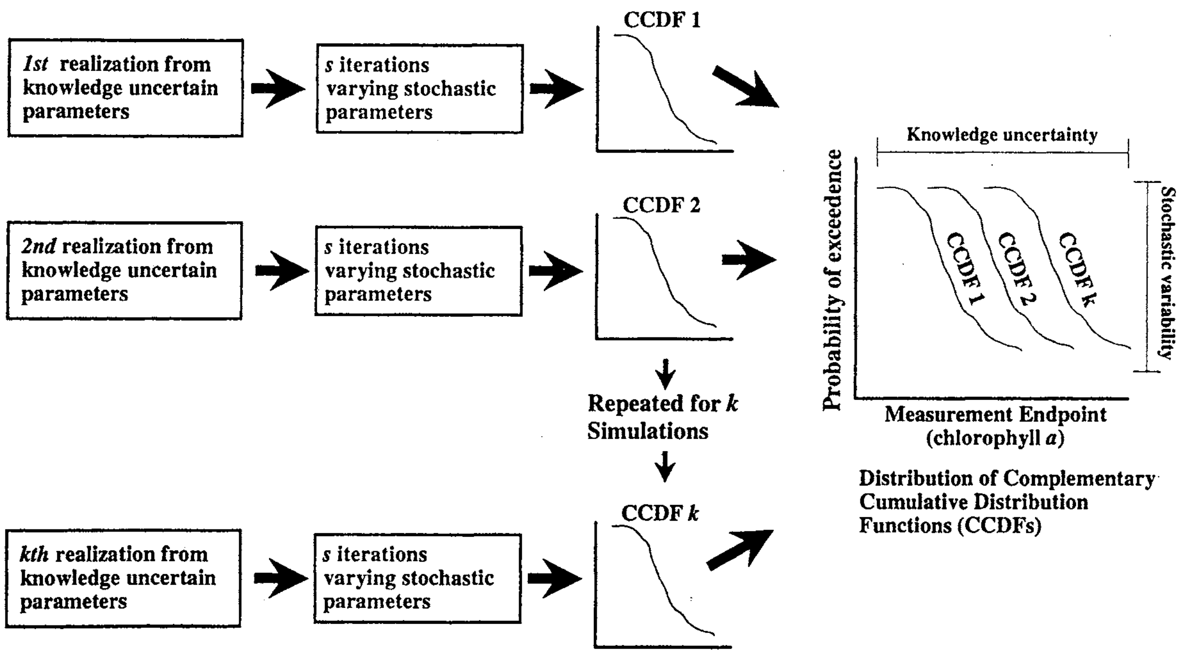

Figure 4.3 Illustration of two-phased Monte Carlo procedure utilized to propagate knowledge uncertainty and stochastic variability separately.

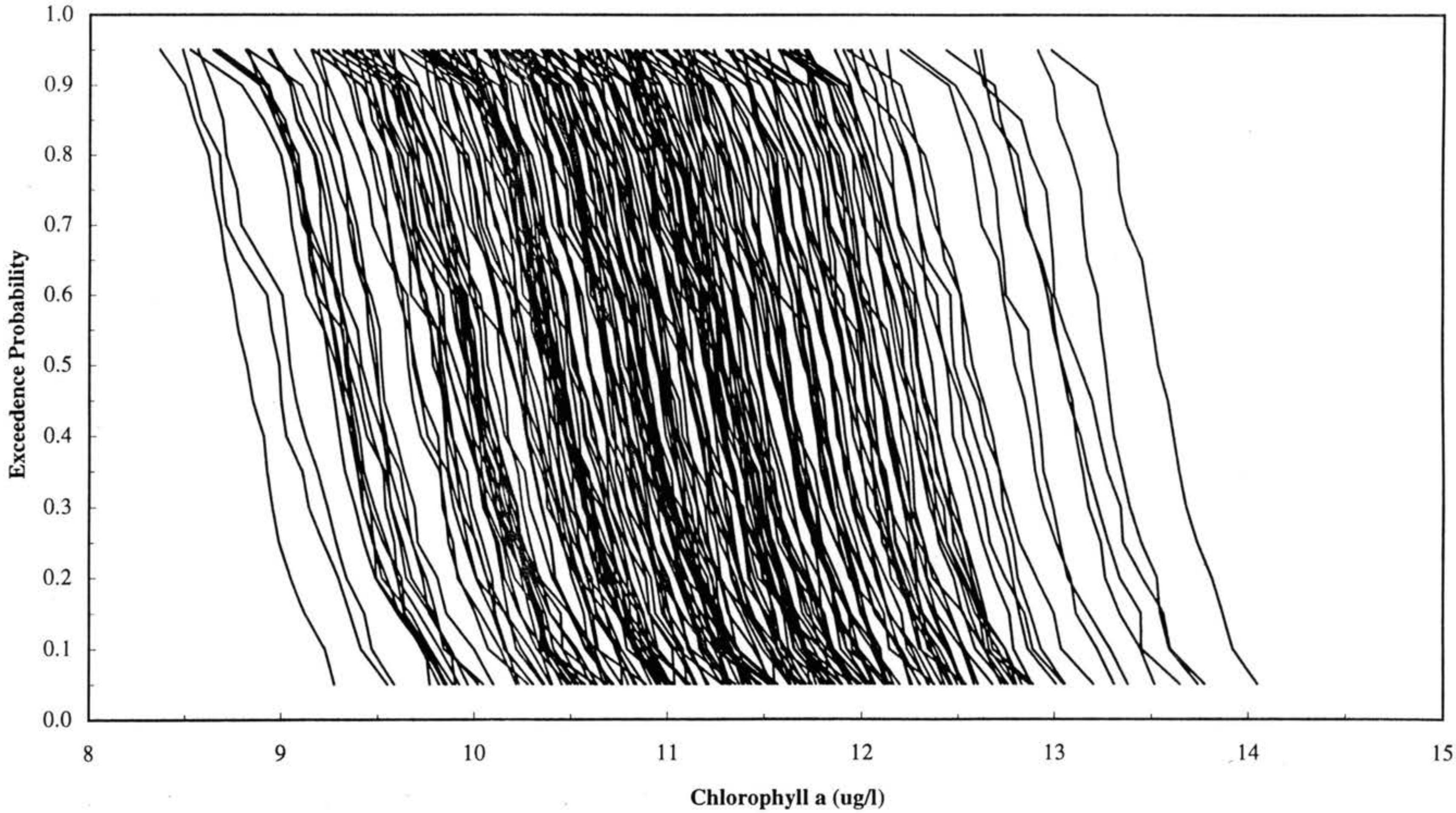

Figure 4.4 Distribution of CCDFs for in-lake chlorophyll *a* estimates with EUTROMOD.

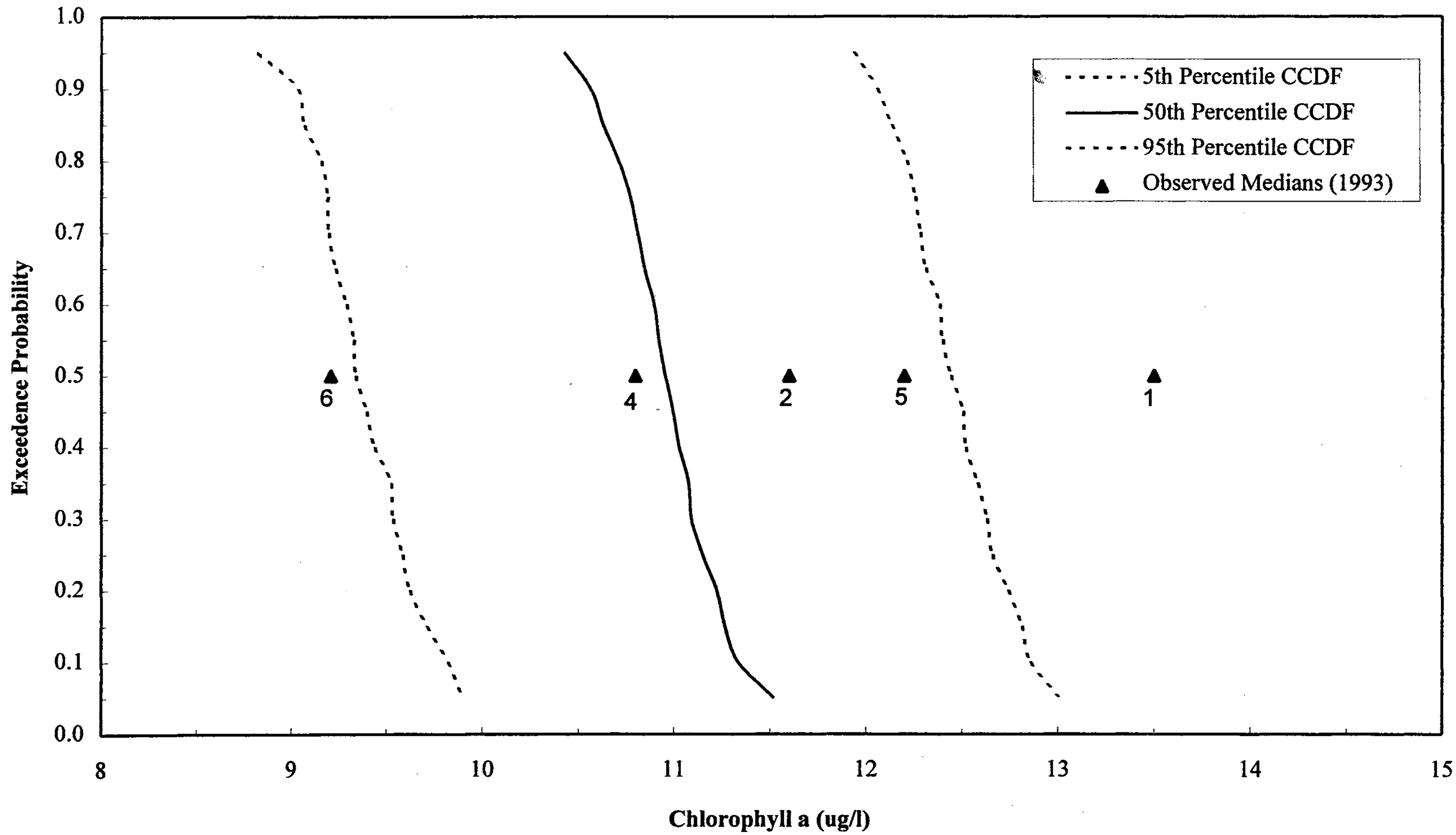

Figure 4.5 Summary of the distribution of CCDFs of in-lake chlorophyll *a* estimates. Observed medians are based on 15 samples at each station throughout 1993 (see Appendix 1 for individual sample values and station locations).

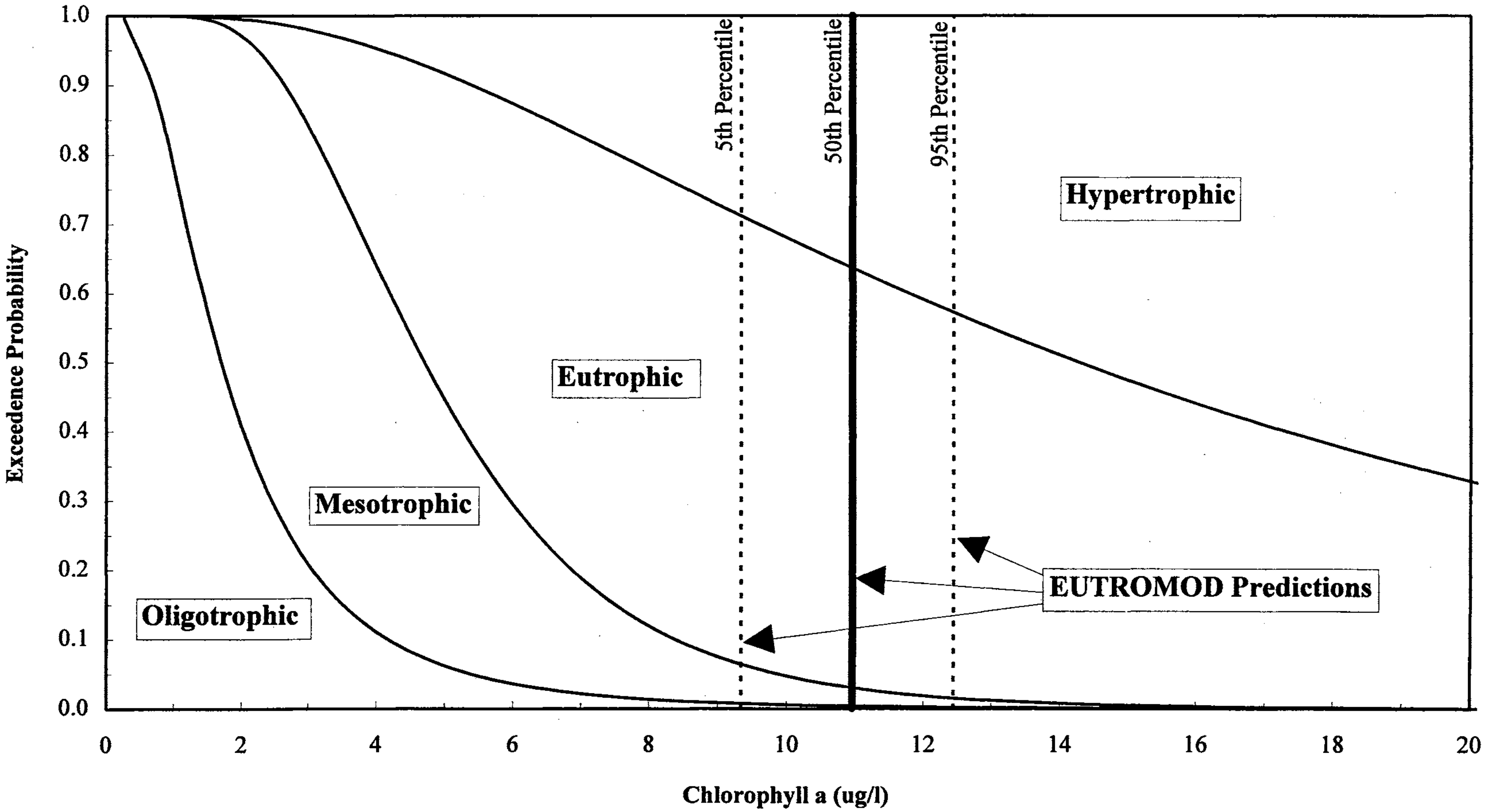

Figure 4.6 Probability of a predicted in-lake chlorophyll *a* concentration falling within a given trophic class based on data presented by Vollenweider (1982). Also shown are predicted median chlorophyll *a* from the 5th, 50th, and 95th percentile CCDFs at the 0.5 exceedence probability.

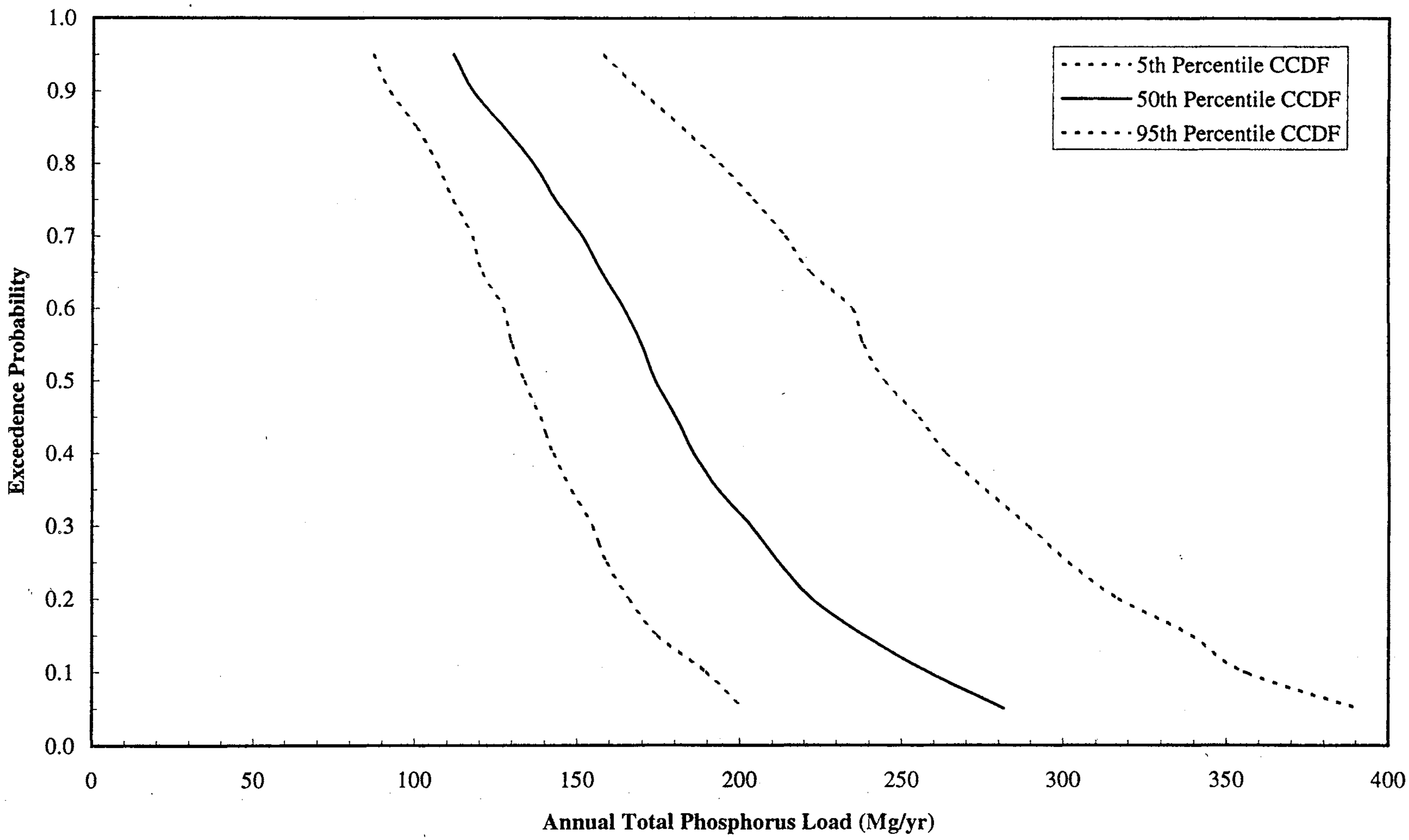

Figure 4.7 Summary of CCDFs of annual total phosphorus load estimates.

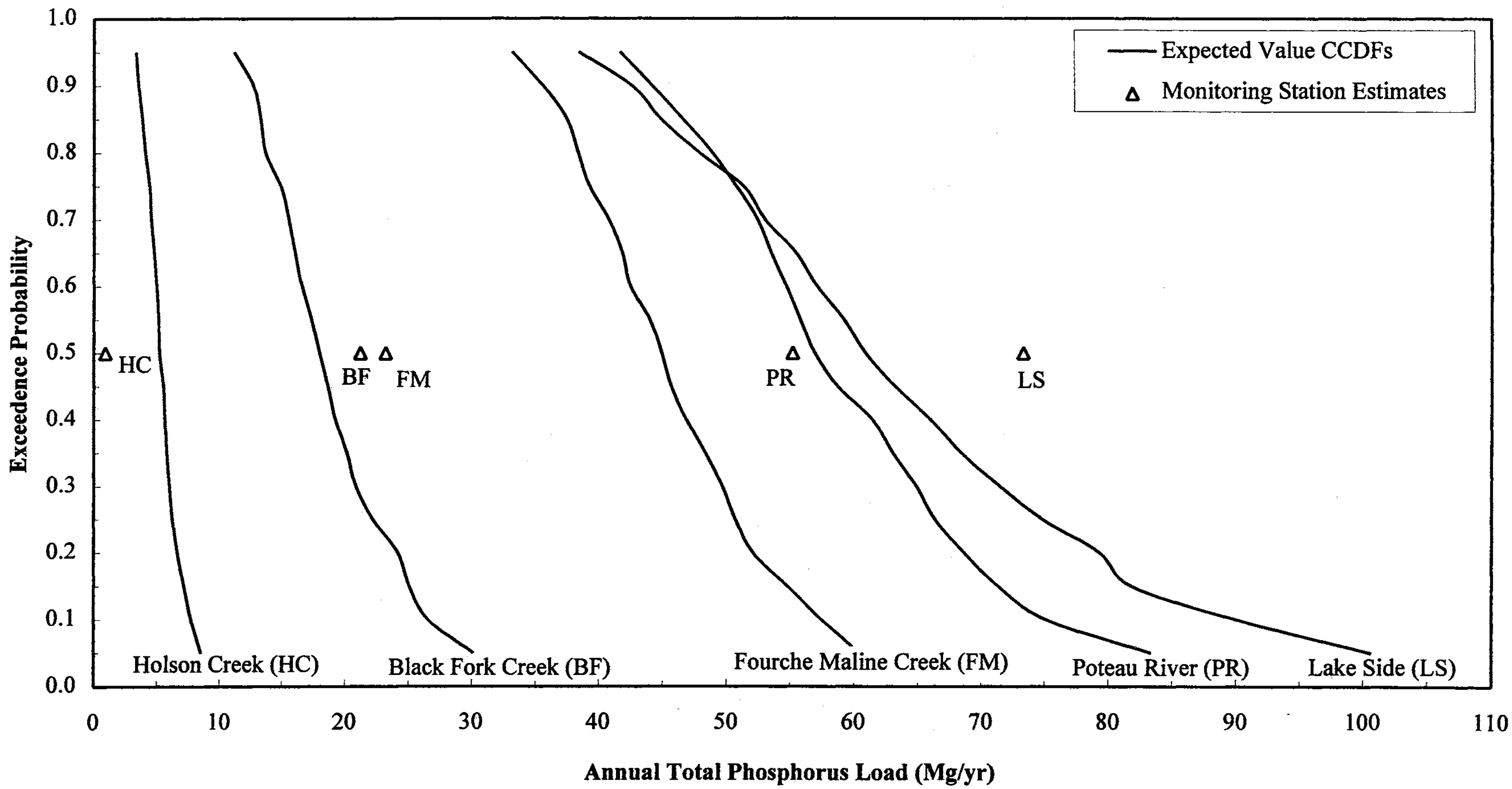

Figure 4.8 Predicted expected value annual phosphorus load CCDFs for the individual subwatersheds compared to annual load estimates based on two years of monitoring data. Details concerning monitoring station estimates can be found in Smolen et al. (1993). HC, BF, FM, and PR estimates are based on 6-week samples within the named stream. LS estimates are based on extrapolations from PR monitoring station data.

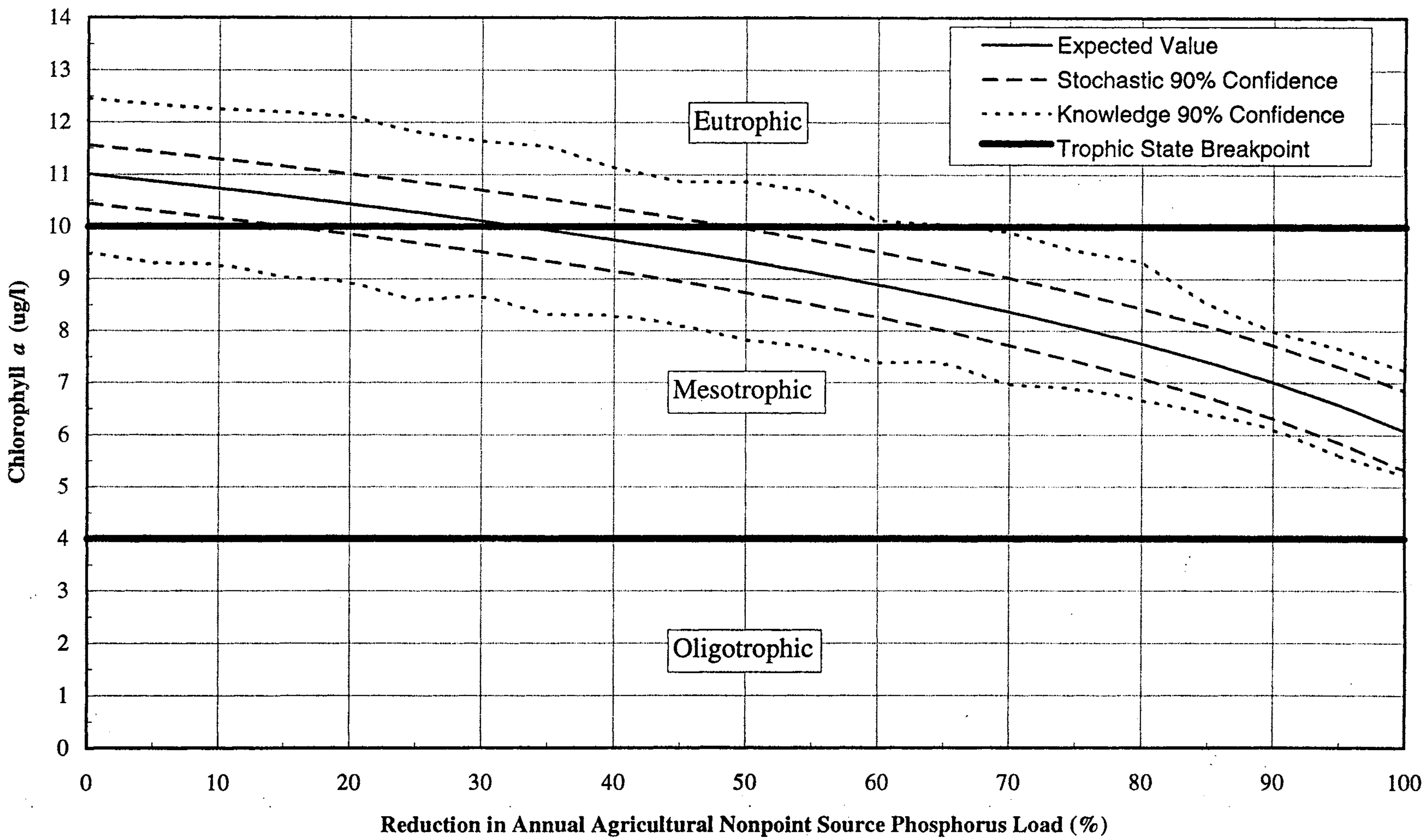

Figure 4.9 In-lake chlorophyll *a* estimates and corresponding trophic state category in response to percentage reductions in annual agricultural nonpoint source phosphorus loads.

CHAPTER 5

RECOMMENDATIONS

The directions for recommended future research include:

1. In terms of future research and data collection for Wister Lake and its watershed, there are two main areas of concern. First, the spreading of poultry manure in the watershed was found to be the most significant source of phosphorus. In addition, the parameters used to describe this source of phosphorus were found to be the most important in terms of output uncertainty as well as the most difficult and uncertain to estimate. Therefore, accurate data on the number of broilers processed in the watershed are needed. In addition, more accurate information is needed concerning where the manure is applied and at what rates, and a thorough inventory of how much of the manure actually remains in the watershed is needed.

   Second, the lake side (LS) area of the watershed was estimated to be the largest source of phosphorus loads to the lake. Unfortunately, it is also the portion of the watershed that has the least amount of data. For instance, there are no monitoring stations within this portion of the watershed; therefore, comparisons between model estimates and monitoring data are difficult at best. Some form of monitoring should be employed in order to adequately quantify the loads and sources from the lake side portion of the Wister Lake watershed.

2. In this study, phosphorus was assumed to be the most significant nutrient in terms of limiting algal growth as well as manageability. Additional analyses are needed concerning other nutrients (nitrogen) and sediments. In fact, several researchers involved with the Wister Lake study have suggested that light (limited due to high suspended solids in the lake) is the limiting growth factor, and, without this limitation, the nutrients in the lake would cause a much more significant problem. More work is needed to address this issue.

3. Chlorophyll *a* and trophic state were chosen as endpoints for this study due to their predictability as well as their perceived importance. However, additional investigation into what the public and elected officials desire from Wister Lake is needed and an endpoint should be defined to reflect these desires. For instance, if the main desire of the public is to reduce the cost of treating drinking water, then possibly only the peak algal growth periods are of concern, in which case an average annual simulation model such as EUTROMOD is inadequate.

4. Further analysis with EUTROMOD or some other H/WQ model should be conducted to address specific best management practice installations in the Wister Lake watershed. In addition, cost analyses should be included to determine the most cost effective combination of management alternatives available to achieve water quality goals.

5. The lake response portion of EUTROMOD is very sensitive to watershed runoff due to its effect on hydraulic retention times. In addition, the runoff coefficient from the Rational Equation is not considered the "cutting edge" technology for

estimating the complexities of the hydrology of watersheds. One option would be to incorporate a more extensive runoff model into EUTROMOD. Another option would be to perform an extensive analysis of observed rainfall and runoff data within the Wister Lake watershed in order to estimate the runoff coefficients (as the ratio of annual runoff to annual rainfall) and to adequately account for the uncertainties and variabilities inherent in the estimations of this factor.

6. The release of phosphorus from bottom sediments may be a significant source of phosphorus within the lake. Additional monitoring is needed to assess the amount of phosphorus in the lake sediments and estimates are needed concerning its release into the water.

7. Much more work is needed to fully understand and quantify uncertainty at the watershed level. In this study, temporal variability (on an annual basis) and parameter knowledge uncertainty were addressed. However, spatial variability was ignored. In addition, error due to the lumping of parameter values was not accounted for. Whether this lumping should be considered parameter error or spatial variability is unclear. In fact, the resulting error is due to spatial variability, but presents itself in the simulations as parameter error. In addition, this error or uncertainty due to lumping could be defined as model error as well. In summary, additional research is needed to define the different types of uncertainty inherent in watershed-level assessment and management as well as to determine ways to adequately account for these uncertainties.

8. Additional research is needed to thoroughly understand the reduction in output uncertainty when performing Monte Carlo-type analyses with distributed

parameter models. Most likely, the reduction in output uncertainty is unique for each model, study area, and discretization level. However, a method for estimating and correcting for this reduction in output uncertainty is needed.

9. The results of the 2-phased Monte Carlo procedure need to be summarized into a single CCDF or PDF, thereby allowing for quantifying risk as a single value.

10. The TMDL and ecological risk assessments were performed in this study using the lake and its trophic state as a management endpoint. However, more often than not, the water bodies managed by state and federal agencies are lotic (streams and rivers). Little data and information are available for assigning endpoints to lotic water bodies with the stressor of concern being nutrients. Additional research is needed to define the unacceptable characteristics of a nutrient stressed stream or river. In addition, simple models such as EUTROMOD must be modified to allow for assessing in-stream impacts.

11. The TMDL concept is inadequate for analysis at the watershed level where both point and nonpoint sources exist. Fortunately, the U.S. EPA allows for flexibility when applying a TMDL to waterbodies impacted by nonpoint sources. However, the TMDL concept should be rebuilt and/or renamed in order to more adequately apply to the watershed-level concerns now facing society.

12. An extensive probability analysis of the data used to develop U.S. EPA's trophic state classification breakpoints would be very useful. As a result, the trophic classification could be presented as uncertain entities and probabilistic expressions for lake trophic state could be presented similar to those presented in Chapter 4 for the open boundary system.

APPENDICES

APPENDIX 1

CHAPTER 2 DETAILS

(Risk Analysis of Total Maximum Daily Loads in an Uncertain Environment Using EUTROMOD)

INPUT PARAMETER DISTRIBUTIONS

The purpose of this section is to present details concerning the input parameter selection process for the *Risk Analysis of Total Maximum Daily Loads in an Uncertain Environment Using EUTROMOD* (Chapter 2). A list of parameters required for input to EUTROMOD and their abbreviations are given in table 2.2. In the paper (Chapter 2), only the distributions used in simulating natural conditions were presented (table 2.3) due to length restrictions. Therefore, the distributions for all parameters used to simulate current conditions are presented in table A1.1. In addition, detailed discussions are presented by parameter under the main data types: climatic, watershed, and lake.

Climatic Data

Precipitation (PREC, PRECCV)

Precipitation data were obtained from the Climdata CD-ROM in the Geography Department at Oklahoma State University. This database is from the National Climatic Data Center and contains statistical weather information for stations throughout the U.S. I retrieved annual precipitation amounts for seven stations within or near the Wister Lake watershed (see Figure 1.1 for station locations).

Data were analyzed statistically within BestFit Version 1.02 (Palisade Corporation, Newfield, NY). Annual precipitation amounts for all stations were found to fit lognormal distributions based on the Kolmogorov-Smirnov (K-S) and the Chi-Square (C-S) goodness of fit tests. Resulting distributions and test results are in table A1.2.

The annual precipitation was treated as having both temporal stochasticity and knowledge uncertainty. The precipitation mean and coefficient of variation were treated as having knowledge uncertainty. Triangular distributions were assigned to PREC and PRECCV based on the range of values found for the seven stations in table A1.2. These knowledge mean and coefficients of variation were then used to define the lognormal distribution used for assigning stochastic variability to precipitation.

The knowledge uncertain PREC and PRECCV variables were correlated at -0.31 based on the rank correlation coefficients estimated through analysis of the seven PREC-PRECCV pairs. The stochastic and knowledge uncertain PRECs were correlated to the stochastic and knowledge USLE R factor values, respectively, based on subjective judgement at a value of 1.0. Although, this was subjectively assigned, later evaluation of 27 years of data from Guthrie, Oklahoma resulted in a rank correlation of 0.90 between observed annual precipitation and rainfall erosivity. Once this new correlation value was determined (after the fact) the model was run using the two different values with no significant change in output distributions.

Precipitation Nutrients (PRECP, PRECN)

Values for the dissolved nutrient content of precipitation were obtained from Sharpley et al. (1985). They determined the chemical composition of rainfall at several rural Oklahoma and north Texas locations over a number of years (1972-1984). Data from the Chickasha, Oklahoma station, which was the closest to the Wister Lake watershed, were used. Since the data used were actual collected data near the study site, a triangular rather than uniform distribution was assumed. The range of values of total phosphorus and total nitrogen concentration were selected from the reported minimum and maximum values in the study. The mode was set to the average values reported in the study (see table A1.1 for resulting distributions).

Watershed Data

Runoff Coefficient (RC)

The EUTROMOD model uses the Rational Equation's runoff coefficient to estimate annual runoff from each land use as a fraction of annual precipitation. Literature values were obtained for the different land uses to estimate a range of possible values (Chow, 1964; Reckhow et al., 1990; Schwab et al., 1981). The values found are given in table A1.3 by literature source and land use. Triangular distributions were subjectively selected to represent these ranges with the modes set based on the author's experienced judgement (see table A1.1 assigned distributions).

USLE Parameters

Rainfall Erosivity (R). This parameter was treated as having both knowledge uncertainty and stochastic variability. Usually, R values are estimated from isoerodent maps (Stewart et al., 1975; Wischmeier and Smith, 1978). The lack of knowledge in picking the R value from an isoerodent map is represented by assigning a triangular distribution to the average annual values. Figure A1.1 is a reproduction of an isoerodent map presented by Stewart et al. (1975). From this map, one might select a value of 520 or attempt to interpolate between 520 and 600 for the Wister Lake watershed. There is much uncertainty and error in such an estimate due to personal bias as well as errors inherent in the development of the iso-value lines from experimental data. Therefore, I chose to represent knowledge uncertainty for the R value as a triangular distribution with a mode equal to the isoerodent line closest to the watershed (520) and a range equal to the next closest isoerodent lines (minimum=430; maximum=600).

Temporal stochasticity was assigned based on analysis of 27 years of observed rainfall erosivity data at an original USLE test plot in Guthrie, Oklahoma and the assertion by Beasley (1972) that annual rainfall erosivity values are lognormally distributed. The observed annual rainfall erosivities from Guthrie, Oklahoma were found to fit a lognormal distribution (fig. A1.2), significant at the α=0.10 level using the K-S and C-S goodness of fit tests. Based on these findings, the stochasticity of rainfall erosivity in the Wister Lake watershed was assumed to be lognormal with a mean obtained from the distribution representing knowledge uncertainty and a coefficient of variation equal to that found for the Guthrie annual rainfall erosivity data (0.67).

Soil Erodibility (K). This parameter was treated as having only knowledge uncertainty. A K factor coverage was generated from the soil data layers within the GRASS GIS. Erodibility values were assigned to each soil type or group in the soils data layer from county soil survey reports from the NRCS and the soils data layer was resampled to create a K factor data layer. Next, by overlaying the K factor data layer with the land use data layer, area-weighted K factors were determined for each land use as required for input to EUTROMOD.

At this point, it is apparent that there are several sources of uncertainty in the K factor estimates. First, there is knowledge uncertainty in that the K factors assigned for each soil type are not known with certainty, they are just estimates. Second, there are errors in the soils data layer due to resolution and registration problems as well as differences between the Oklahoma and Arkansas portions. Third, there is error due to lumping of the K factors within each land use. This lumping could be considered spatial variability. In fact, it is possible to determine the distribution of K factors within each land use using the GIS. However, since only knowledge uncertainty was being accounted for, the error due to lumping was ignored. This was an important assumption and was addressed in the "Recommendations" portion of this dissertation.

Stewart et al. (1975) presented a table that assigns K factor based on soil texture and organic matter content. The distributions for K factor knowledge uncertainty were assigned as uniform distributions having a range equivalent to the average range of values presented by Stewart et al. (1975) for sandy loam soils since most soils in the watershed were similar. Uniform distributions were assigned as being centered on the area-weighted average K factor value with a minimum and maximum value ±0.08 (metric units; see table A1.1).

Topographic Factor (LS). This parameter was treated as having only knowledge uncertainty. As with the K factor, this parameter is based on lumping within each land use and, therefore, has multiple sources of uncertainty. A slope data layer was created from the elevation data layer within the GIS. This slope data layer was then overlaid with the land use data layer and area-weighted average slopes were computed for each land use. Again, the distribution of slopes within each land use was assumed to be spatially variable, not knowledge uncertain, and was ignored for this analysis.

The slope lengths were assigned for each land use based on Oklahoma NRCS's technical guidance which assigns slope lengths based on slopes and soil texture (e.g. for sandy loams: 0-1%=600', 1-3%=500', 3-5%=400', 5-8%=300', and 8-12%=200'; percent slopes greater than 12% were assumed to have a slope length of 100').

The distributions for knowledge uncertainty were assigned to the topographic factors using the follows process:

1. Determine area-weighted average percent slope for each land use. (i.e. 4.7% for pasture)
2. Assign a slope length for each land use based on NRCS technical guidance and percent slope assigned in (1) (i.e. 400' for pasture).
3. From Wischmeier and Smith (1978), identify the percent slopes bracketing that selected in (1) above (i.e. see table A1.4 as an example for pasture; 5% and 6% chosen).
4. Also, in Wischmeier and Smith (1978) identify the slope lengths that bracket that chosen in (2) above (i.e. see table A1.4 as an example for pasture, 300' and 500' chosen).
5. Assign a uniform distribution for the LS factor based on the minimum and maximum values bracketed (i.e. see table A1.4 as an example for pasture, minimum=0.621 and maximum=1.20).

See table A1.1 for distributions determined for each land use based on this methodology.

The above method was devised to ensure that the topographic factors were assigned wide ranges in order to adequately represent the uncertainties involved. In estimating LS factor values the uncertainties in parameter estimation can result from the following:

1. Errors in resolution and/or registration problems in the elevation data layer.
2. Errors incurred during creating slopes from the elevation data layer.
3. Lumping the slopes and assigning an area-weighted average by land use.
4. Error in assigning slope lengths. This is always a difficult procedure without actual field reconnaissance.
5. Biases and interpolation errors incurred while estimating LS factors from slope lengths and percent slopes from tables or figures (Wischmeier and Smith, 1978).
6. The LS factor is a purely empirical relationship with little or no physical basis (Moore and Burch, 1986). Therefore, there are also errors in the regression equation used to develop the relationship.

Cropping Factor (C). This parameter was treated as having only knowledge uncertainty. The distribution was assumed to be uniform since the range of possible values was based purely on literature values, not on measured data within or near the study area. The C factors were estimated as annual average values and the minimum and maximum values were assigned based on several references (Wischmeier and Smith, 1978; Reckhow et al., 1992; Haan et al., 1994). The assigned ranges for each land use are shown in table A1.1.

Practice Factor (P). The management practice factor was assumed to be deterministic (equal to unity) for all land uses.

Land Use Areas (AREA)

Land use areas were computed using the land use data layer in the GRASS GIS. All land uses were considered deterministic except for pasture and manured pasture. However, the total amount of pasture (non-manured and manured) was considered deterministic. The land use areas are given in table A1.5 for the entire watershed as well as within each of the five major subwatersheds.

The effects of the poultry industry prevalent in the watershed were incorporated into the model by estimating the amount of pasture spread with poultry litter. This manured pasture was then included as a separate land use in the model with higher nutrient loading factors.

The area estimates for manured pasture were based on an estimate of broilers produced in the watershed on an annual basis, estimates of the nutrient content of poultry manure, and an estimate of typical application rates. Obviously, there was much uncertainty inherent in these estimates. However, at the time of this study, this was the best data available. The knowledge uncertainty was assigned a triangular distribution with the modes estimated as shown in table A1.6. The maximum or upper bound of the triangular distribution was selected based on estimates made by the NRCS and the Oklahoma Cooperative Extension Service for a hydrologic unit area proposal (NRCS and CES, 1991 unpublished proposal). The minimum bound on the triangular distribution was computed by substituting the value used in column (5) in table A1.6 with the value minus one standard deviation (standard deviation=0.053; from ASAE Standards, 1990).

The amount of total phosphorus spread on pasture (84 kg P/ha-yr or approximately 6.7 Mg/ha of litter) was estimated based on a discussion with Storm (1994, personal communication) and as referenced in Sharpley et al. (1994). The poultry litter is typically spread on fields based on nitrogen needs of the crop (~18 kg N/ha-yr; Sharpley, 1994). Unfortunately, this results in an excess application of phosphorus in terms of crop needs.

Loading Factors (LFPDIS, LFPSED, LFNDIS, LFNSED)

The loading factors for phosphorus and nitrogen, dissolved and sediment-bound, were treated as having knowledge uncertainty. The ranges for dissolved as well as sediment-bound nutrients were obtained from the literature as detailed in table A1.7. However, references specific to the study area were found for sediment-bound nutrients, but not for dissolved nutrients. Therefore, dissolved nutrient inputs were assigned to uniform distributions and sediment-bound were assigned to triangular distributions.

Enrichment Ratios (ENP, ENN)

The phosphorus and nitrogen enrichment ratios were treated as having knowledge uncertainty. Both were assumed to be triangular distributions based on ranges found in the literature (Haith and Tubbs, 1981; Dean, 1983; Blalock, 1987). The modes were set based on the best estimates suggested by Haith and Tubbs (1981) (see table A1.1 for final distributions).

Trapping Factors (TF)

The USLE estimates edge-of-field sediment losses. However, the movement of sediment and sediment-bound nutrients from source areas to receiving water body is a complex process involving many rainfall-runoff events, deposition, resuspension, and chemical transformations, among other things. The quantity of sediment estimated to have been lost from source areas (USLE) is usually higher than the amount actually transported to the watershed outlet or the lake. Typically, a large fraction of the sediment and sediment-bound pollutants are trapped within the watershed (Reckhow et al., 1992). EUTROMOD accounts for this loss of sediment and attached pollutants with "attenuation zones." For each attenuation zone, a trapping factor (TF) is defined as the fraction of gross sediment that is "trapped" within an area, thereby, not being delivered to the watershed outlet or lake.

In EUTROMOD, these attenuation zones and their TFs are a simple lumped method of modeling a variety of complex processes. This "catch-all" concept can be used to account for natural trapping effects within watersheds as well as management practices, including (but not limited to) agricultural BMPs, sedimentation basins, riparian zones, wetlands, and slope changes.

I used sediment delivery ratios to estimate trapping efficiencies. Sediment delivery ratios (DR) are estimated as the amount of sediment delivered to the point of measurement divided by the mass of soil loss due to gross erosion (i.e. USLE estimates in this case). Estimated DRs can be used to estimate trapping efficiencies for use in EUTROMOD as: $TF = 1\text{-}DR$.

EUTROMOD allows for the definition of up to nine attenuation zones into which the land use category areas can be distributed. The Wister Lake watershed consists of four main subwatersheds flowing into the lake and the area adjacent to the lake (lake side; see fig. 1.1). Five attenuation zones were defined based on these four subwatersheds and the lake side area. The land use digital layer was overlaid onto a subwatershed coverage and amounts of each land use within each subwatershed were determined (table A1.5). The amounts of each land use category per subwatershed were then distributed among the five attenuation zones for input to the model.

Delivery ratios have been estimated based on a variety of factors, including geomorphology, watershed size, and distance from source to stream. The estimated DRs and TFs for each subwatershed based on three separate methods, watershed area (Haan et al., 1994), watershed relief ratio (Maner, 1958), and mainstem stream distance-based (Reckhow et al., 1989) are shown in table A1.8. The areas, relief ratios, and distances along the mainstem stream were determined using routines within the GRASS GIS.

The distance-based method of Reckhow et al. (1989) was developed using data from Oklahoma, Texas, and southern Kansas. Delivery ratios are calculated as: $ln(DR)=1.01-0.34ln(d)$; where d is half the length of the mainstem stream (m). These estimates were taken as being "site specific" and triangular distributions were employed with the distance-based estimates as the mode, the relief ratio-based estimate as the minimum, and the high end of the area-based estimate as the maximum. Since the range of estimates was based on different methods of estimating trapping factors, they were correlated to each other subjectively (0.50) under the assumption that one would use the same method of estimation for all attenuation zones.

Septic Systems

Number of People (SEPNUM). The U.S. EPA included ten residences (equivalent to 35 per capita-yr; an average of 3.5 persons per residence) and one park (30 per capita-yr) while computing nutrient loads to Wister Lake for the National Eutrophication Survey (U.S. EPA, 1977). For most applications it is reasonable to consider only those systems located a few hundred meters from the lake and tributary shorelines (Reckhow et al., 1992).

Since no information was available concerning the present level of septic systems and their locations relative to shorelines, U.S. EPA's estimate was used as a starting point. The distribution for SEPNUM was assumed to be uniform with a minimum equal to U.S. EPA's estimate (65 per capita-yr). The maximum of the range was based on doubling the number of residences to 20 (70 per capita-yr) and increasing the park estimate by 20 per capita-yr resulting in an upper bound of 120 per capita-yr. These distributions were set subjectively, but conservatively.

Nutrient Load (SEPP, SEPN). The septic nutrient loadings (kg/person-yr) were estimated from two sources (U.S. EPA, 1977; Reckhow et al., 1980). Triangular distributions were assigned with the U.S. EPA estimates as the mode and the range based on the range of possible values presented in Reckhow et al. (1980). The resulting distributions are given in table A1.1.

Soil Retention Factors (RETP, RETN). The percentage of phosphorus and nitrogen from septic tanks retained in the soil were assigned to a uniform distribution based on the range of values found in the literature (Metcalf and Eddy, 1979; Reckhow et al., 1980).

Point Source Information (PSQ, PSP, PSN)

Nine significant point sources were located within the Wister Lake watershed. Table A1.9 lists these facilities, two in Arkansas and seven in Oklahoma, their average and design flows, and estimated nutrient concentrations. Flow and concentration data were available for the two facilities in Arkansas from recent studies performed by consulting firms (Storm et al., 1994). The Oklahoma point sources were determined from the Oklahoma Water Quality Management Plan of 1993 and, although important information on flow, populations, and location were provided, no information on nutrient concentrations and little information concerning treatment type were available. Therefore, secondary treatment was assumed and nutrient concentrations were estimated from Thomann and Mueller (1987) for the point sources in Oklahoma.

EUTROMOD only allows for the inclusion of one flow, one phosphorus concentration, and one nitrogen concentration as point source input. Therefore, all flows were summed and flow-weighted average nutrient concentrations were computed for input to the model. The distributions for all were assumed to be uniform. The minimum flow was set equal to the sum of the average flows (1.62 MGD) while the maximum was set to the design flow summation (1.83 MGD). The ranges of the nutrient concentrations were set based on coefficients of variation (0.33 to 0.38) for point source nutrient concentrations presented by Reckhow and Chapra (1983). Therefore, the nutrient concentration distribution ranges were set to plus or minus one standard deviation from the flow-weighted average concentrations computed in table A1.9. The assigned distributions are provided in table A1.1.

Lake Data

Lake Area and Depth (LAREA, LDEPTH)

Finally, information concerning lake morphometry (surface area and mean depth) and lake evaporation rates were treated as having knowledge uncertainty. Surface elevation and lake volume data were obtained from the U.S. Army Corps of Engineers

(Christine Altendorf, 1995 personal communication). Surface elevation and lake area data were obtained from the Oklahoma Water Resources Board (OWRB, 1985 unpublished data). These relationships are shown in figure A1.3.

The desired normal pool elevations are 144.9 m (475.5 ft) from December through May and 145.7 m (478 ft) from June through November (Christine Altendorf, 1995 personal communication). However, until recently the pool elevation from December through May was 144.7 (474.6 ft), but a congressional directive demanded that it be raised. Therefore, the range of values due to knowledge uncertainty of pool elevations was set from 144.7 m to 145.7 m. This range was then used to estimate a range of volumes (49.4 to 77.0 m^3*10^6) and areas (27.11 to 29.68 km^2) using figure A1.3. Average lake depth was computed for the ranges of volume and area as *volume/area* (1.8 to 2.6 m). The lake area (LAREA) and depth (LDEPTH) distributions were assumed to be uniformly distributed. The knowledge uncertainty distributions for lake area and average depth were correlated at 1.0 based on analysis of the data.

Lake Evaporation (LEVAP)

Annual lake evaporation was also treated as having knowledge uncertainty. A triangular distribution was assigned based on analysis of data for one station at the Wister Lake dam from the Climdata CD-ROM in the Geography Department at Oklahoma State University.

OBSERVED LAKE DATA

In Chapters 2 and 4 the simulated in-lake chlorophyll a concentrations were compared with observed data from an on-going U.S. EPA Clean Lake Project (Oklahoma Water Resources Board, unpublished data). In the previous comparisons (fig. 2.5 and 4.5) only the 1993 observed median in-lake chlorophyll *a* concentrations were included. This was due to the fact that EUTROMOD estimates annual or growing season median conditions and the available monitoring data only had one full year of data (1993). Table A1.10 lists all of the data available from the five sampling stations at different locations on the lake as monitored for an ongoing Clean Lakes Project. The sampling station locations within the lake are shown in Figure A1.4.

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Table A1.1 List of EUTROMOD inputs and distribution assignments for Chapter 2 simulations.

Parameter	*Units*	*Distribution **
Parameters with Stochastic Variability		
PREC	cm/yr	Lognormal(*k*†{PREC},*k*{PRECCV})
RE	MJ-mm/ha-h	Lognormal(*k*{R},0.60)
Parameters with Knowledge Uncertainty		
(Climatic Data)		
PREC	cm/yr	Triangular(112,120,123)
PRECCV	cm/yr	Triangular(0.23,0.25,0.28)
PRECN	mg/l	Triangular(0.16,0.21,0.22)
PRECP	mg/l	Triangular(0.012,0.015,0.021)
(Watershed Data)		
RC[cropland]	fraction	Triangular(0.2,0.4,0.5)
RC[pasture]	fraction	Triangular(0.15,0.35,0.45)
RC[manured pasture]	fraction	Triangular(0.15,0.35,0.45)
RC[forest]	fraction	Triangular(0.1,0.25,0.4)
RC[urban]	fraction	Triangular(0.25,0.7,0.95)
RC[disturbed]	fraction	Triangular(0.5,0.6,0.9)
RC[wetlands/water]	fraction	=1.0
R	MJ-mm/ha-h	Triangular(430,520,600)
K[cropland]	Mg/ha per unit R	Uniform(0.40,0.56)
K[pasture]	Mg/ha per unit R	Uniform(0.40,0.56)
K[manured pasture]	Mg/ha per unit R	Uniform(0.40,0.56)
K[forest]	Mg/ha per unit R	Uniform(0.27,0.43)
K[urban]	Mg/ha per unit R	none
K[disturbed]	Mg/ha per unit R	Uniform(0.29,0.45)
K[wetlands/water]	Mg/ha per unit R	=0
LS[cropland]	ratio	Uniform(0.62,1.2)
LS[pasture]	ratio	Uniform(0.62,1.2)
LS[manured pasture]	ratio	Uniform(0.62,1.2)
LS[forest]	ratio	Uniform(1.56,2.81)
LS[urban]	ratio	n/a
LS[disturbed]	ratio	Uniform(0.58,1.21)
LS[wetlands/water]	ratio	=0
C[cropland]	ratio	Uniform(0.22,0.29)
C[pasture]	ratio	Uniform(0.012,0.043)
C[manured pasture]	ratio	Uniform(0.012,0.043)
C[forest]	ratio	Uniform(0.0001,0.001)
C[urban]	ratio	n/a
C[disturbed]	ratio	Uniform(0.66,1.3)
C[wetlands/water]	ratio	=0
P[*all land uses*]	ratio	=1
AREA[cropland]	ha	=240
AREA[pasture]	ha	=58730-AREA[manured pasture]
AREA[manured pasture]	ha	Triangular(3094,5094,11094)
AREA[forest]	ha	=192171
AREA[urban]	ha	=2053
AREA[disturbed]	ha	=621
AREA[wetlands/water]	ha	=3800
LFPDIS[cropland]	mg/l	Uniform(0.3,0.8)
LFPDIS[pasture]	mg/l	Uniform(0.15,0.3)

Table A1.1 (continued)

Parameter	*Units*	*Distribution*
LFPDIS[manured pasture]	mg/l	Uniform(1,5)
LFPDIS[forest]	mg/l	Uniform(0.006,0.012)
LFPDIS[urban]	mg/l	Uniform(0.12,0.38)
LFPDIS[disturbed]	mg/l	Uniform(0.03,0.06)
LFPDIS[wetlands/water]	mg/l	=0
LFPSED[cropland]	mg/kg	Triangular(200,300,400)
LFPSED[pasture]	mg/kg	Triangular(200,300,400)
LFPSED[manured pasture]	mg/kg	Triangular(800,800,1100)
LFPSED[forest]	mg/kg	Triangular(200,300,400)
LFPSED[urban]	mg/kg	n/a
LFPSED[disturbed]	mg/kg	Triangular(150,250,300)
LFPSED[wetlands/water]	mg/kg	=0
ENP	ratio	Triangular(1.19,1.5,3.74)
LFNDIS[cropland]	mg/l	Uniform(1.8,3)
LFNDIS[pasture]	mg/l	Uniform(2,3)
LFNDIS[manured pasture]	mg/l	Uniform(7,16)
LFNDIS[forest]	mg/l	Uniform(0.06,0.19)
LFNDIS[urban]	mg/l	Uniform(1.5,2.6)
LFNDIS[disturbed]	mg/l	Uniform(0.5,1)
LFNDIS[wetlands/water]	mg/l	=0
LFNSED[cropland]	mg/kg	Triangular(900,1200,2000)
LFNSED[pasture]	mg/kg	Triangular(900,1200,2000)
LFNSED[manured pasture]	mg/kg	Triangular(1900,1900,4000)
LFNSED[forest]	mg/kg	Triangular(900,1200,2000)
LFNSED[urban]	mg/kg	n/a
LFNSED[disturbed]	mg/kg	Triangular(470,600,620)
LFNSED[wetlands/water]	mg/kg	=0
ENN	ratio	Triangular(1.08,2,5)
TF[Poteau River]	ratio	Triangular(0.78,0.92,0.97)
TF[Black Fork]	ratio	Triangular(0.65,0.9,0.97)
TF[Holson Creek]	ratio	Triangular(0.4,0.86,0.96)
TF[Fourche Maline Creek]	ratio	Triangular(0.8,0.91,0.97)
TF[Lake Side]	ratio	Triangular(0.8,0.85,0.97)
SEPNUM	per capita-yr	Uniform(65,120)
SEPP	kg P/person-yr	Triangular(0.74,1.28,3)
SEPN	kg N/person-yr	Triangular(2.15,3.2,8.2)
RETP	fraction	Uniform(0.4,0.7)
RETN	fraction	Uniform(0.3,0.45)
PSQ	MGD	Uniform(1.62,1.83)
PSP	mg/l	Uniform(4.94,10.6)
PSN	mg/l	Uniform(9,17.9)
(Lake Data)		
LAREA	km^2	Uniform(27.11,29.68)
LDEPTH	m	Uniform(1.82,2.59)
LEVAP	m/yr	Triangular(1.0,1.3,1.8)

* Distribution parameters are: Lognormal(mean, coefficient of variation); Triangular(minimum, mode, maximum); and Uniform(minimum, maximum).

† Parameters are obtained from knowledge distribution (k).

Table A1.2 Distributional assignments and goodness of fit tests for annual precipitation from seven weather stations in or near the Wister Lake watershed.

Station	Number of Observations (years)	Lognormal Fit Mean (cm)	Lognormal Fit Coefficient of Variation	K-S* Calculated	K-S Test Statistic (α=0.10)	K-S Test Result	C-S† Calculated	C-S Test Statistic‡ (α=0.10)	C-S Test Result
Fanshawe, OK	43	121	0.25	0.12	0.19	Accept H_o§	3.1	9.2	Accept H_o
Heavener, OK	40	121	0.25	0.09	0.19	Accept H_o	3.5	6.2	Accept H_o
Parks, AR	34	120	0.23	0.12	0.21	Accept H_o	4.8	6.2	Accept H_o
Waldron, AR	42	120	0.25	0.09	0.19	Accept H_o	4.6	6.2	Accept H_o
Wilburton, OK	29	123	0.28	0.19	0.23	Accept H_o	7.0	9.2	Accept H_o
Wister, OK	30	112	0.23	0.08	0.22	Accept H_o	0.6	7.8	Accept H_o
Zoe, OK	34	122	0.24	0.13	0.21	Accept H_o	3.7	9.2	Accept H_o

* Kolmogorov-Smirnov goodness of fit test.

† Chi-Square goodness of fit test.

‡ $\chi^2_{0.9,v}$; where v is degrees of freedom (k-p-1; k=number of class intervals, p=number of parameters estimated (2))

§ The null hypothesis being tested is that the data are from the specified probability distribution.

Table A1.3 Runoff coefficients found in literature.

Source	Land use	Minimum	Maximum
Chow (1964)	Cropland	0.20	0.50
	Pasture	0.15	0.45
	Forest	0.10	0.40
	Urban-Lawns	0.05	0.35
	Urban-Business	0.50	0.95
	Urban-Residential	0.25	0.75
	Urban-Industrial	0.50	0.90
Reckhow et al. (1990)	Cropland	0.10	0.40
	Pasture	0.10	0.35
	Forest	0.05	0.25
Schwab et al. (1981)	Cropland	0.18	0.66
	Pasture	0.02	0.23
	Forest	0.02	0.15

Table A1.4 Detail of a portion of Wischmeier and Smith's (1978) table as an example of assigning LS factor distributions.

Percent	Slope Length (feet)				
Slope	200	300	400	500	600
3	0.354	0.400	0.437	0.466	0.492
4	0.528	0.621	0.697	0.762	0.820
5	0.758	0.928	1.070	1.200	1.310
6	0.952	1.170	1.350	1.500	1.650

Note: The shaded area is shown as an example of the range assigned for pasture land.

Table A1.5 Land use amounts by subwatershed and for the entire Wister Lake watershed.

Watershed	Area* (ha)	Cropland (ha)	Pasture† (ha)	Manured Pasture (ha)	Forest (ha)	Urban (ha)	Disturbed (ha)	Wetlands/ Water (ha)
Poteau River	69540	0	18290	1445	48506	575	35	689
Fourche Maline Creek	69181	212	18965	655	47744	1068	191	346
Black Fork	50927	0	3253	595	46992	43	0	44
Holson Creek	18097	0	825	151	17113	0	0	8
Lakeside	49871	28	12303	2248	31817	367	395	2713
Totals	257616	240	53636	5094	192172	2053	621	3800

* All areas are presented as entered into EUTROMOD ignoring significant digit convention.

† Pasture and manured pastured areas based on mode of input distribution representing knowledge uncertainty.

Table A1.6 Calculations for estimating the amount of manured pasture in the Wister Lake watershed.

(1) County, State	(2) Broilers per year	(3) Weight per Bird (kg)	(4) Total Broiler Weight (kg)	(5) Total Phosphorus as Manure (kg/1000 kg animal/day)	(6) Total Phosphorus as Manure (kg/day)	(7) Total Phosphorus as Manure (kg/yr)	(8) Pasture Land Required to apply 84 kg/ha (75 lb/ac) per year
LeFlore, OK	25000000	0.9	22500000	0.3	6750	303750	3616
Latimer, OK	256000	0.9	230400	0.3	69	3110	37
Scott, AR	10000000	0.9	9000000	0.3	2700	121500	1446
Total Watershed	35256000	0.9	31730400	0.3	9519	428360	5100

Descriptions by column:

Column 1: Counties within the Wister Lake watershed with poultry production.

Column 2: Estimate of number of broiler produced per year in portion of county included in the Wister Lake watershed (Jim Britton, 1994 personal communication.

Column 3: Typical live animal mass per broiler (ASAE Standards (ASAE D384.1); ASAE (1990)).

Column 4: Total broiler weight per year [column (2) * column (3)].

Column 5: Total phosphorus produced as fresh manure per 1,000 kg live animal mass per day (ASAE D384.1).

Column 6: Total phosphorus produced as fresh manure per day [column (4) * column (5)].

Column 7: Total phosphorus produced as fresh manure per year, assuming 6 flocks per year and each bird is in house for 45 days [column (6) * 45] (Jim Britton, 1994 personal communication).

Column 8: Amount of pasture required to spread the estimated phosphorus produced as manure at a typical annual rate of 84 kg/ha (75 lb/ac). This rate is actually based on the nitrogen needs of the pasture [column (7) / 84.0] (D.E. Storm, 1994 personal communication; Sharpley et al., 1994).

Table A1.7 Range of values found in the literature for nutrient loading factors.

Dissolved Loading Factors: Uniform Distributions

	Phosphorus (mg/l)			Nitrogen (mg/l)		
Land Use	Minimum	Maximum	References*	Minimum	Maximum	References
Cropland	0.300	0.800	4	1.80	3.00	4
Pasture	0.150	0.300	4	2.00	3.00	4
Manured Pasture	1.000	5.000	4,5	7.00	16.00	4
Forest	0.006	0.012	4	0.06	0.19	4
Disturbed	0.030	0.060	4	0.50	1.00	4
Urban	0.120	0.380	4	1.50	2.60	4

Sediment-Bound Loading Factors: Triangular Distributions

	Phosphorus (mg/kg)				Nitrogen (mg/kg)			
Land Use	Minimum	Maximum	Mode	References	Minimum	Maximum	Mode	References
Cropland	200	400	300	1,2,3,5	900	2000	1200	3,5
Pasture	200	400	300	1,2,3,5	900	2000	1200	3,5
Manured Pasture	800	1100	800	1,2,3,5	1900	4000	1900	3,5
Forest	200	400	300	1,2,3,5	900	2000	1200	3,5
Disturbed	150	300	250	1,2,3,5	470	620	600	3,5
Urban†	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a

* References:
(1) Abernathy et al. (1983)
(2) Brinlee and Wilson (1981)
(3) Daniel et al. (1993)
(4) Reckhow et al. (1990)
(5) Sharpley et al. (1991)

† Urban land use requires only dissolved nutrient loading factors.

Table A1.8 Delivery ratio and trapping factor determination.

Watershed	*Area-Based Estimate**				*Relief Ratio Based Estimate* †			*Distance-Based Estimate* ‡		
	Area (ha)	Area (mi^2)	DR§ (ratio)	TF‖ (ratio)	Relief Ratio	DR (ratio)	TF (ratio)	1/2 Mainstem Length (m)	DR (ratio)	TF (ratio)
Poteau River	69500	268	0.03-0.10	0.90-0.97	0.012	0.22	0.78	27500	0.08	0.92
Fourche Maline Creek	69200	267	0.03-0.10	0.90-0.97	0.01	0.20	0.80	21000	0.09	0.91
Black Fork Creek	50900	197	0.03-0.12	0.88-0.97	0.021	0.35	0.65	16000	0.10	0.90
Holson Creek	18100	70	0.04-0.20	0.80-0.96	0.04	0.60	0.40	7000	0.14	0.86
Lakeside	49719	192	0.03-0.12	0.88-0.97	0.01	0.20	0.80	5000	0.15	0.85

* Delivery ratio based on watershed area (Figure 8.25, Haan et al., 1994).

† Delivery ratio based on watershed relief ratio (Maner, 1958).

‡ Delivery ratio based on one-half the length of the mainstem stream (Reckhow et al., 1988).

§ Delivery ratio.

‖ Trapping factor (1-DR).

Table A1.9 Point sources in the Wister Lake watershed

Facility Name	Average Flow (MGD)	Design Flow (MGD)	Phosphorus (mg/l)	Nitrogen (mg/l)	Receiving Subwatershed	Treatment Type
Arkansas						
City of Waldron	0.48	0.48	3.8	12.0	Poteau River	oxidation pond, post aeration
Tyson Foods	0.626	0.626	10.6	7.7	Poteau River	activated sludge, lagoons
Oklahoma						
Cedar Lake Park	0.0001	0.024	6.4	17.1	Black Fork Creek	aerated lagoon
Eastern State	0.065	0.065	8.7	23.8	Fourche Maline Creek	lagoon
Ouachita Correct. Cntr.	0.022	0.04	8.7	23.8	Black Fork Creek	lagoon
Red Oak PWA	0.068	0.09	8.7	23.8	Fourche Maline Creek	lagoon
Wilburton PWA, NE	0.144	0.24	8.7	23.8	Fourche Maline Creek	lagoon
Wilburton PWA, S	0.06	0.085	8.7	23.8	Fourche Maline Creek	lagoon
Wilburton PWA	0.15	0.18	6.4	17.1	Fourche Maline Creek	aerated lagoon
Total Flows =	**1.62**	**1.83**				
	Flow Weighted Average Conc. =		**7.8**	**13.4**		

Table A1.10 Observed chlorophyll *a* concentrations from Clean Lakes Project.**

Date	Chlorophyll *a* Concentration (ug/l)				
	Station 1	Station 2	Station 4	Station 5	Station 6
16-Dec-92	4.3	6.8	3.3	1.9	0.0
6-Jan-93	5.2	6.3	5.5	10.6	9.3
11-Feb-93	26.9	34.9	154.5	13.0	2.7
3-Mar-93	3.8	7.8	6.2	4.0	4.7
8-Apr-93	18.4	22.9	20.7	11.4	5.2
12-May-93	13.6	11.6	7.2	1.7	5.4
26-May-93	13.4	19.8	15.0	11.0	17.2
9-Jun-93	7.3	7.4	5.6	13.4	4.9
23-Jun-93	14.4	10.5	12.0	15.2	9.1
15-Jul-93	18.4	16.9	9.2	31.0	28.1
28-Jul-93	10.8	11.5	14.7	20.1	22.8
12-Aug-93	17.3	14.9	12.3	20.0	27.6
25-Aug-93	23.9	7.5	9.0	11.1	20.7
15-Sep-93	20.0	18.3	12.2	26.1	15.0
13-Oct-93	9.3	9.0	10.8	24.2	27.2
23-Nov-93	1.9	12.7	8.3	1.6	0.8
15-Dec-93	2.0	3.2	3.7	2.9	2.2
27-Jan-94	10.4	15.7	13.4	12.1	37.2
24-Feb-94	6.6	20.4	6.5	4.1	2.2
23-Mar-94	22.5	22.1	3.6	12.8	7.1
20-Apr-94	7.0	5.9	2.7	27.2	17.8
4-May-94	9.6	8.6	14.5	3.6	8.0
18-May-94	6.0	6.6	5.9	16.5	13.1
15-Jun-94	20.0	14.7	20.5	16.2	21.8
29-Jun-94	15.0	12.3	27.9	24.3	39.6

** Oklahoma Water Resources Board, unpublished data.

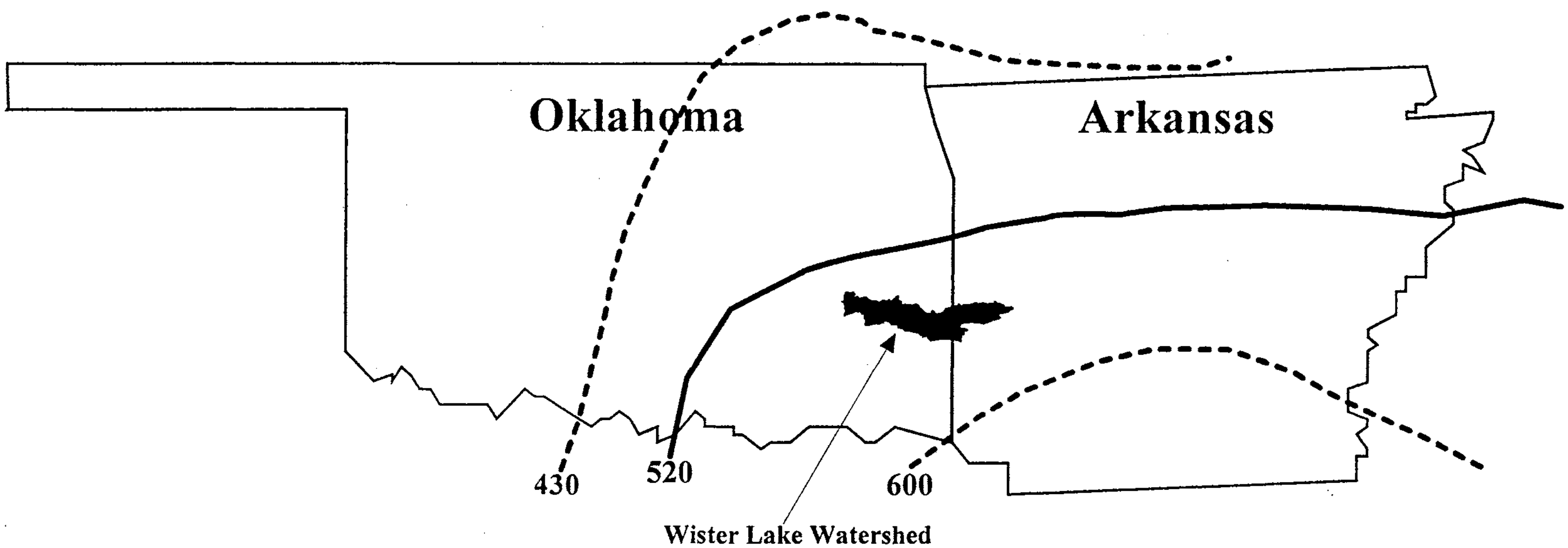


Figure A1.1 Location of iso-value lines of average annual rainfall erosivity. Values are in metric units (MJ-mm/ha-h). Based on Stewart et al. (1975).

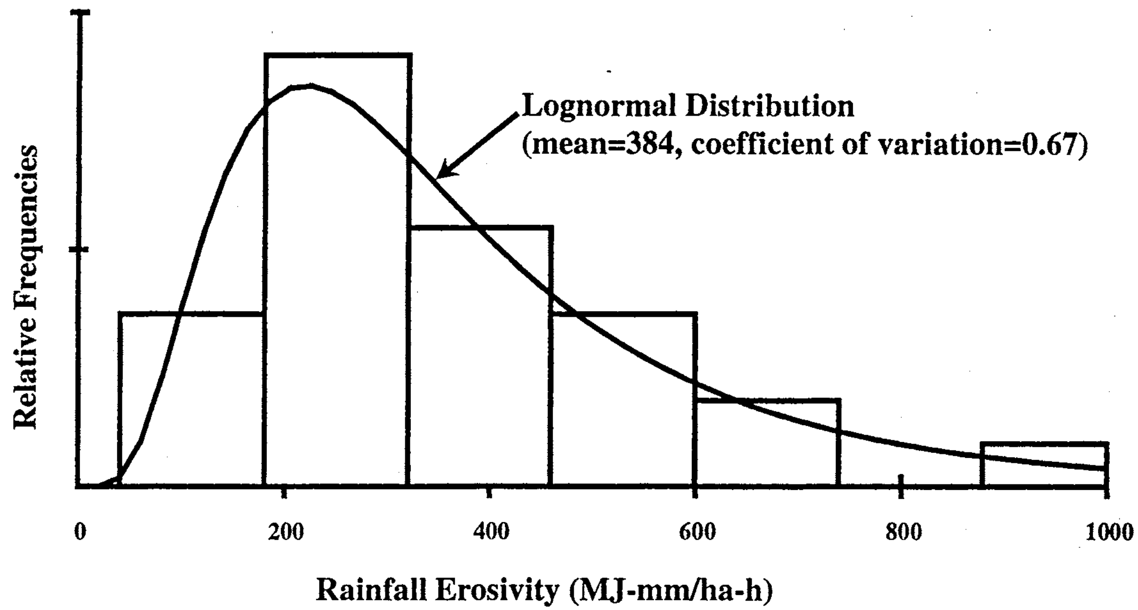


Figure A1.2 Observed relative frequencies and fitted lognormal distribution for annual average rainfall erosivities from Guthrie, Oklahoma (H_o accepted at α=0.10 level for both K-S and C-S goodness of fit tests).

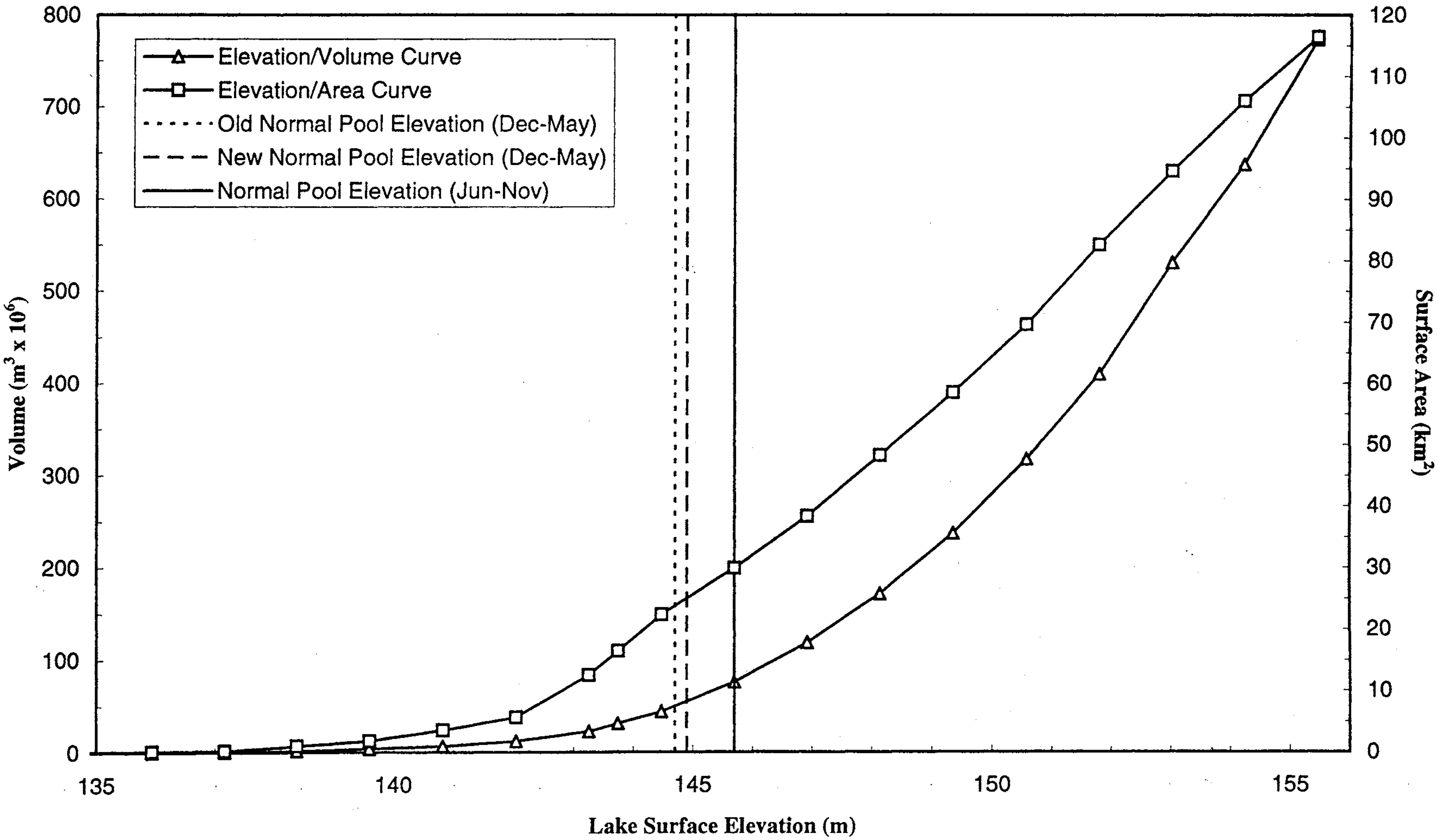
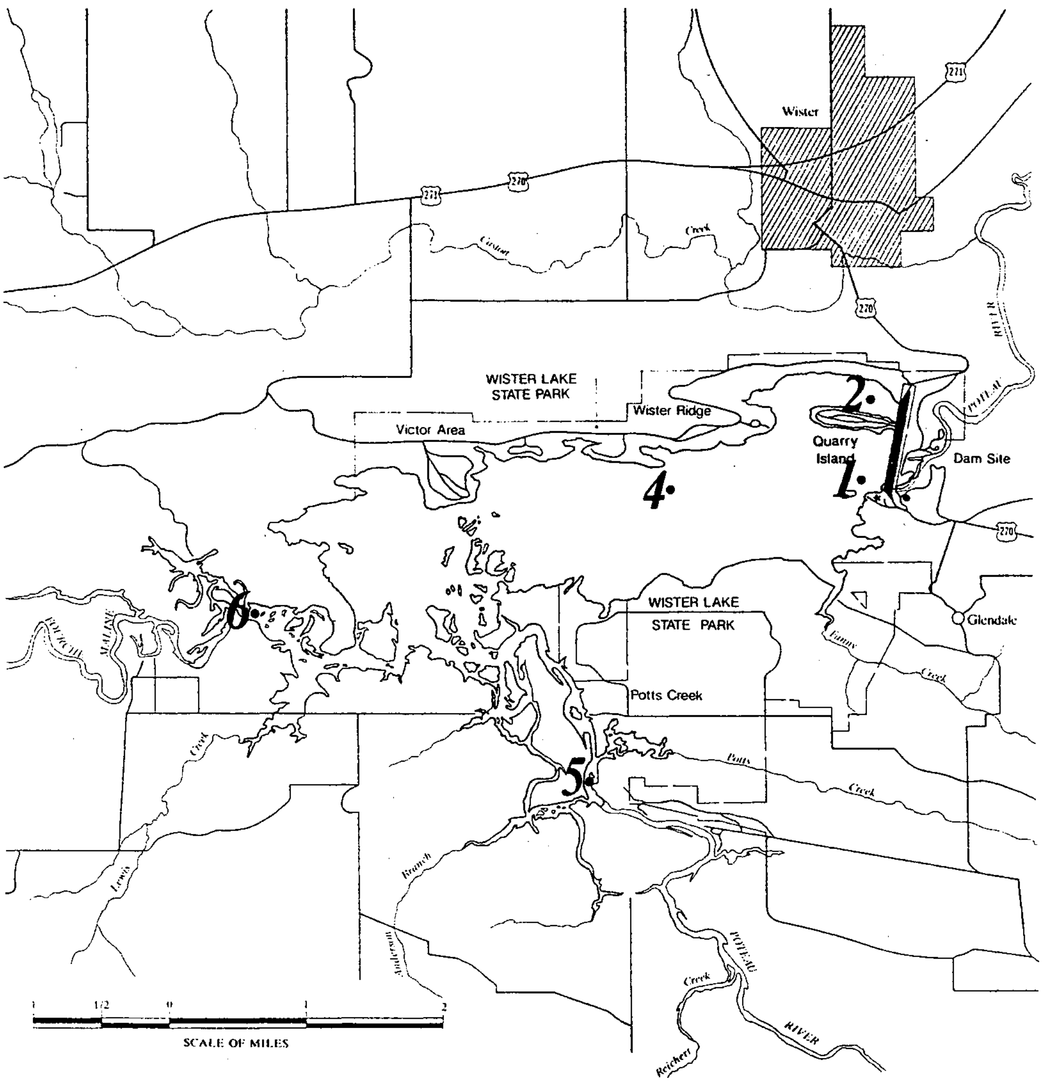


Figure A1.3 Elevation-area-volume relationships for Wister Lake.


Wister
WISTER LAKE
STATE PARK
Wister Ridge
Victor Area
Quarry
Island
Dam Site
WISTER LAKE
STATE PARK
Glendale
Potts Creek
1.
2.
4.
5.
6.
SCALE OF MILES

APPENDIX 2

CHAPTER 3 DETAILS

(Uncertainty and the USLE)

GUTHRIE, OKLAHOMA PLOT DATA

Twenty seven years of measured rainfall, runoff, and soil loss data were obtained from the National Soil Erosion Research Laboratory at Purdue University for four original USLE test plots in Guthrie, Oklahoma. The observed rainfall, runoff, rainfall erosivity (R), and sediment loss are shown in tables A2.1 through A2.4. In addition, yearly estimates of USLE are provided as estimated by Risse et al. (1993). The yearly soil loss estimates of Risse et al. (1993) were used to produce the empirical distribution functions (EDFs) in figures 3.5 through 3.8. Finally, the mean and median estimates for all the parameters in the tables are provided. The purpose for this is to highlight the differences between the mean and median annual soil loss due to the skewed nature of the annual soil loss distribution.

ADDITIONAL OUTPUT: DISCRETIZATION STUDY

An important result of the USLE study was that output uncertainty or variance was reduced merely due the act of discretization. Figure A2.1 shows the soil loss CCDFs for plot 1-1 as an undivided plot and as a discretized plot (four subdivisions). Note that these CCDFs were due to knowledge uncertainty only. The CCDF for the discretized plot showed a marked decrease in variability or uncertainty. The reason for this reduction in variance was shown mathematically in Chapter 3.

The CCDFs are distribution-free distributions or EDFs and the ends of the distributions represent the distribution-free 90% confidence interval. However, in order to evaluate the reduction of uncertainty due to level of discretization it proves useful to inspect confidence intervals in terms of the confidence interval equation under assumptions of normality (Haan, 1977):

$$CI = \bar{x} - t_{1-\frac{\alpha}{2},n-1}\, s_{\bar{x}} \qquad \text{(A2.1)}$$

where $\bar{x}$ is the mean, t is the value from the t distribution with a confidence interval of $100(1-\alpha)$, and $s_{\bar{x}}$ is the standard deviation of the mean. The standard deviation is computed as the square root of variance.

Chapter 3 results indicated that when discretization is performed the output variance is approximately $1/m$ times the original variance, where m is the number of subdivisions. Therefore, we would expect the confidence intervals for the divided plots to be $\sqrt{1/m}$ times the undivided confidence intervals. In fact, inspection of figure A2.1 verified these expectations. The 90% confidence interval for the undivided plot is approximately 20 Mg/ha. Therefore, we would expect the 90% confidence interval for the discretized plot to be $\sqrt{1/4}$ (or 0.5) times the that of the undivided plot. The 90% confidence of the CCDF for the discretized plot's soil loss is approximately 10 Mg/ha wide, or 0.5 times the confidence interval of the undivided plot's CCDF. This estimate of confidence interval reduction will be used to compare the results from Chapter 2 and Chapter 4 simulations in Appendix 3.

REFERENCES

Risse, L.M. M.A. Nearing, A.D. Nicks, and J.M. Laflen. 1993. Error assessment in the Universal Soil Loss Equation. *Soil Science Society of America Journal* 57:825-833.

Table A2.1 Observed data and USLE soil loss estimates for plot 1-1 in Guthrie, Oklahoma.

Plot Characteristics:		*USLE Factors (metric; Risse et al., 1993):*	
Width (m) =	1.8	RE Factor =	(by year in table)
Length (m) =	11.1	K Factor =	0.28
Slope (%) =	7.7	LS Factor =	0.57
Tillage =	Up/Down	C Factor =	0.59
Crop Type =	Cotton	P Factor =	1.00

Year	Observed Rainfall (mm)	Observed Runoff (mm)	Observed RE (Mg-mm/ha-hr)	Observed Soil Loss (Mg/ha)	USLE Soil Loss (Mg/ha)*
1930	855	99	429	48	41
1931	742	77	259	18	25
1932	950	182	586	107	56
1933	798	140	457	29	44
1934	897	176	655	36	63
1935	806	75	486	20	46
1936	545	66	301	12	29
1937	613	17	266	4	25
1938	797	49	313	4	30
1939	598	45	200	3	19
1940	845	32	371	6	35
1941	missing data	185	515	20	49
1942	893	72	397	7	38
1943	641	54	131	5	12
1944	797	53	303	2	29
1945	862	134	548	36	52
1946	701	52	236	4	23
1947	706	70	303	6	29
1948	687	59	273	17	26
1949	1168	320	1018	539	97
1950	719	55	273	4	26
1951	917	91	673	12	64
1952	527	5	157	0	15
1953	842	56	344	3	33
1954	389	0	41	0	4
1955	663	21	176	1	17
1956	658	77	346	7	33
Average	754	84	372	35	36
Median	769	66	313	7	30

* As estimated by Risse et al. (1993) using the factors defined above. These estimates were used to create empirical distribution function (EDF) in Figure 3.5.

Table A2.2 Observed data and USLE soil loss estimates for plot 1-2 in Guthrie, Oklahoma.

Plot Characteristics:		*USLE Factors (metric; Risse et al., 1993):*	
Width (m) =	1.8	RE Factor =	(by year in table)
Length (m) =	44.3	K Factor =	0.28
Slope (%) =	7.7	LS Factor =	1.13
Tillage =	Up/Down	C Factor =	0.59
Crop Type =	Cotton	P Factor =	1.00

Year	Observed Rainfall (mm)	Observed Runoff (mm)	Observed RE (Mg-mm/ha-hr)	Observed Soil Loss (Mg/ha)	USLE Soil Loss (Mg/ha)*
1930	855	86	429	32	81
1931	742	100	259	57	49
1932	950	142	586	196	111
1933	798	135	457	74	87
1934	897	197	655	85	124
1935	806	91	486	105	92
1936	545	76	301	56	57
1937	613	33	266	14	50
1938	797	76	313	46	59
1939	598	42	200	12	38
1940	845	82	371	33	70
1941	missing data	229	515	61	98
1942	893	117	397	24	75
1943	641	104	131	21	25
1944	797	65	303	10	58
1945	862	195	548	247	104
1946	701	76	236	10	45
1947	706	133	303	35	57
1948	687	102	273	209	52
1949	1168	415	1018	832	193
1950	719	97	273	107	52
1951	917	181	673	110	128
1952	527	24	157	6	30
1953	842	142	344	45	65
1954	389	10	41	2	8
1955	663	102	176	34	33
1956	658	172	346	46	66
Average	754	119	372	93	71
Median	769	102	313	46	59

* As estimated by Risse et al. (1993) using the factors defined above. These estimates were used to create empirical distribution function (EDF) in Figure 3.6.

Table A2.3 Observed data and USLE soil loss estimates for plot 1-3 in Guthrie, Oklahoma.

Plot Characteristics:		*USLE Factors (metric; Risse et al., 1993):*			
Width (m) =	1.8	RE Factor =	(by year in table)		
Length (m) =	22.1	K Factor =	0.28		
Slope (%) =	7.7	LS Factor =	0.80		
Tillage =	Up/Down	C Factor =	0.59		
Crop Type =	Cotton	P Factor =	1.00		
Year	Observed Rainfall (mm)	Observed Runoff (mm)	Observed RE (Mg-mm/ha-hr)	Observed Soil Loss (Mg/ha)	USLE Soil Loss (Mg/ha)*
1930	855	112	429	39	58
1931	742	98	259	26	35
1932	950	136	586	153	79
1933	798	123	457	33	61
1934	897	176	655	34	88
1935	806	72	486	41	65
1936	545	69	301	28	40
1937	613	23	266	4	36
1938	797	68	313	23	42
1939	598	24	200	1	27
1940	845	58	371	25	50
1941	missing data	182	515	26	69
1942	893	75	397	10	53
1943	641	73	131	11	18
1944	797	58	303	7	41
1945	862	171	548	113	74
1946	701	69	236	14	32
1947	706	87	303	15	41
1948	687	86	273	91	37
1949	1168	328	1018	420	137
1950	719	65	273	13	37
1951	917	120	673	39	90
1952	527	13	157	3	21
1953	842	75	344	9	46
1954	389	6	41	2	5
1955	663	60	176	18	24
1956	658	124	346	16	46
Average	754	94	372	45	50
Median	769	75	313	23	42

* As estimated by Risse et al. (1993) using the factors defined above. These estimates were used to create empirical distribution function (EDF) in Figure 3.7.

Table A2.4 Observed data and USLE soil loss estimates for plot 1-8 in Guthrie, Oklahoma.

Plot Characteristics:		*USLE Factors (metric; Risse et al., 1993):*			
Width (m) =	1.8	RE Factor =	(by year in table)		
Length (m) =	22.1	K Factor =	0.28		
Slope (%) =	7.7	LS Factor =	0.80		
Tillage =	Up/Down	C Factor =	1.00		
Crop Type =	Fallow	P Factor =	1.00		
Year	Observed Rainfall (mm)	Observed Runoff (mm)	Observed RE (Mg-mm/ha-hr)	Observed Soil Loss (Mg/ha)	USLE Soil Loss (Mg/ha)*
1930	855	196	429	41	98
1931	742	160	259	14	59
1932	950	272	586	31	133
1933	798	254	457	45	104
1934	897	293	655	65	149
1935	806	225	486	77	111
1936	545	162	301	35	68
1937	613	145	266	65	61
1938	797	243	313	51	71
1939	598	116	200	23	45
1940	845	237	371	94	84
1941	missing data	360	515	31	117
1942	893	204	397	12	90
1943	641	121	131	7	30
1944	797	134	303	3	69
1945	862	276	548	38	125
1946	701	94	236	7	54
1947	706	176	303	20	69
1948	687	150	273	8	62
1949	1168	379	1018	343	231
1950	719	130	273	6	62
1951	917	223	673	8	153
1952	527	31	157	1	36
1953	842	139	344	4	78
1954	389	33	41	1	9
1955	663	75	176	1	40
1956	658	137	346	7	79
Average	754	184	372	38	85
Median	769	162	313	20	71

* As estimated by Risse et al. (1993) using the factors defined above. These estimates were used to create empirical distribution function (EDF) in Figure 3.8.

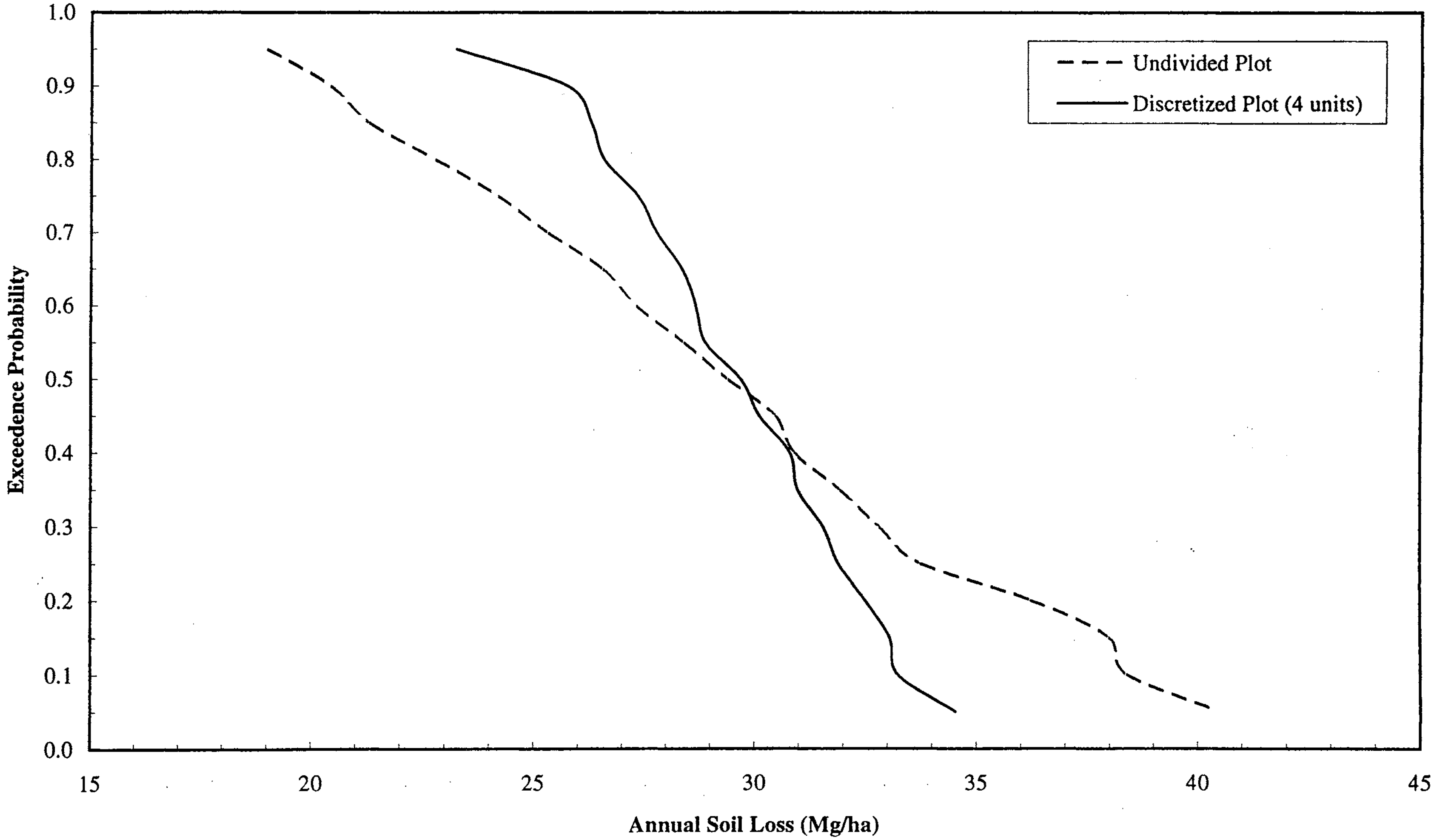


Figure A2.1 Comparison of soil loss CCDFs for plot 1-1 discretized into four subdivisions and not discretized.

APPENDIX 3

CHAPTER 4 DETAILS

(A Watershed-Level Ecological Risk Assessment Methodology)

SENSITIVITY ANALYSIS

Introduction and Literature Review

Chapter 2 simulations were performed with *all* model input parameters treated as being uncertain, assigned probability distributions, and included in Monte Carlo analyses. Many of these parameters had little effect on output variability due to lack of importance in the model structure or due to the small range of possible values (low uncertainty). An important step in any risk assessment or modeling activity is a sensitivity analysis (Gardner et al., 1981; Downing et al., 1985; Morgan and Henrion, 1992; Yeh and Tung, 1993; Burmaster and Anderson, 1994; Hammonds et al., 1994; Helton, 1994; MacIntosh et al., 1994). Burmaster and Anderson (1994) suggested the use of sensitivity analysis to identify the inputs suitable for probabilistic treatment.

The @Risk software provides two different analytical techniques for performing sensitivity analyses. Both techniques make use of the fact that with a Monte Carlo procedure, there are many outputs as well as a set of inputs corresponding to each output. The first technique is a form of regression analysis. With this analysis, sampled input variable values are regressed against output values, leading to a measurement of sensitivity by input variable. The second technique is a rank correlation calculation (Iman and Conover, 1982). In this analysis, rank correlation coefficients are calculated between the output values and each set of sampled input values.

Many techniques have been utilized to perform sensitivity analyses. MacIntosh et al. (1994) performed linear regression for each individual input versus output from Monte Carlo simulation results and ranked the input parameters by the r^2 of the regression. They explained that this was a "measure of the amount of uncertainty in the expected distribution explained by uncertainty in the parameter." Helton (1994), also using results from a Monte Carlo analysis, used partial rank correlation coefficients to rank input parameters in order of importance. Correlations greater than 0.5 were assumed to be significant. They suggested that ranks help remove the effects of nonlinearities.

Hammonds et al. (1994) used squared rank correlation coefficients and adjusted them to 100% in order to determine the most influential input parameters. Yeh and Tung (1993) listed simple correlation coefficients, rank correlation coefficients, partial correlation coefficients, and partial rank correlation coefficients as useful measures of sensitivity. They concluded that the partial simple and partial rank correlations were the most useful. The correlation coefficients "indicate the strength of the association between inputs and outputs" (Yeh and Tung, 1993). They suggested that parameters found to be insignificant in regression can be considered "constants" in uncertainty analyses.

Morgan and Henrion (1992) discussed simple sensitivity and normalized sensitivity or elasticity, defined as:

$$U_S(x,y) = \left[\frac{\partial y}{\partial x}\right]_{X^0} \tag{A3.1}$$

$$U_E(x,y) = \left[\frac{\partial y}{\partial x}\right]_{X^0} \times \frac{x^0}{y_0} \tag{A3.2}$$

where U_S and U_E are the simple and normalized sensitivity (or elasticity), respectively, x is input, y is output, and X^0 indicates that the derivatives are evaluated at the values of the nominal or "base-case" scenario. They stated that the problem with simple sensitivity is that it depends on the scale, or units of measurement of x and y. The normalized sensitivity corrects for this problem by defining the changes in x and y in relative terms, as a fraction of their nominal values. However, a drawback to both of these as measures of uncertainty importance is that they consider only the slopes of the response surface, and ignore the degree of uncertainty in each input (Morgan and Henrion, 1992). For instance, an input that has a small sensitivity (in terms of model structure) but a large uncertainty (do to lack of knowledge) might be very important in influencing output uncertainty.

Morgan and Henrion (1992) recommended correlation coefficients for use in sensitivity analyses from Monte Carlo simulations. Correlation coefficients were cited as being a truly global measure of "uncertainty importance." They provide a good estimate of the effect of uncertainty in input on uncertainty in output, averaged over all possible combinations of values of the other inputs, weighted by their probabilities. In addition, they concluded that rank-order correlations are good measures of the strength of monotonic relations, whether linear or not.

Gardener et al. (1981) recommended using simple correlation coefficients for Monte Carlo simulations to rank model parameters according to contributions to prediction uncertainty. They ranked sensitivities in terms of output-input combinations and selected the top 10 for probabilistic consideration. Downing et al. (1985) used partial rank-order correlation citing the measures ability to account for nonlinearity and correctly incorporate monotonicity.

Sensitive Input Parameters

Based on the review of literature concerning sensitivity analysis and the available techniques provided within the @Risk software, uncertainty importance for this study was defined using the rank correlation coefficient technique. It is important to note that this analysis was performed only on the parameters having knowledge uncertainty; the two stochastic parameters (PREC and R) were assumed to be important in defining stochasticity and automatically included as probabilistic parameters in Chapter 4 simulations.

The EUTROMOD model was run for 225 iterations while varying only the knowledge uncertain parameters. Simulations were performed with the model as used in Chapter 2 (without the subwatershed modeling capability). Any input parameters found to be important were entered into the subwatershed-version of the model as being probabilistic within each of the subwatersheds. The 13 parameters found to be significant in defining output uncertainty are shown in table A3.1. The important parameters were ranked based on their correlation coefficient with in-lake chlorophyll *a* output; the correlations are also shown in relation to total phosphorus load. Significance of the correlation coefficients was determined using:

$$t = r_s\sqrt{\frac{n-2}{1-r_s^2}} \tag{A3.3}$$

where t is the test statistic used to consult a t-distribution table, r_s is the rank correlation coefficient, and n is the number of data points. Determining a t-value from a t-distribution table (Haan, 1977) at a 95% confidence level (1.97), inserting 225 for n, and solving for r_s, a correlation greater than or equal to 0.13 was considered significant. An input parameter was selected if its correlation coefficient was greater than 0.13 in terms of in-lake chlorophyll *a* or total phosphorus load output. These parameters (table A3.1) were selected for probabilistic consideration in the Chapter 4 simulations; all others were treated as constants.

To ensure that the parameters selected adequately accounted for output uncertainty, output CCDFs from the model with all inputs treated as probabilistic and those resulting from considering only the parameters given in table A3.1 were compared (fig. A3.1 and A3.2 for chlorophyll *a* and total phosphorus loads, respectively). The model used in Chapter 2 (without subwatershed capability) was run 225 times while varying only knowledge uncertain parameters. There is very little difference between the CCDFs and it appears that the inputs most important in influencing output uncertainty were correctly chosen.

MODEL MODIFICATIONS

The EUTROMOD model was converted from a share-ware spreadsheet program to Microsoft Excel Version 5.0 for use in this study. In addition, for the simulations in Chapter 5, the model was modified to allow for simulating up to ten subwatersheds. This was done by copying the watershed input and output portion of the spreadsheet ten times and providing a section for accumulating the loads from these subwatersheds to estimate total loads for the entire watershed. The total loads are then input into the lake model portion of EUTROMOD which was not modified in any way. This modification was made to allow for comparisons with the monitoring station data described in Chapter 1. However, this modification also requires that all watershed characteristic inputs be entered by subwatershed, thereby greatly increasing the number of input parameters that must be estimated.

MODEL INPUT

Introduction

There are two main differences between the model input for Chapter 2 and Chapter 4: 1) only the input parameters found to significantly influence output uncertainty were treated as probabilistic inputs for the Chapter 4 simulations and 2) all watershed descriptive inputs were required by subwatershed, lumped by land use.

Probabilistic Input

Stochastic Variability

PREC and R were again treated as temporally stochastic parameters. However, in Chapter 2 simulations with these two parameters were treated as having knowledge uncertainty as well. The knowledge uncertain aspect of these parameters was not found to significantly contribute to output uncertainty, therefore PREC and R were treated as having only stochastic variability for Chapter 4 simulations.

The R factor was treated as lognormal with a mean equal to the isoerodent line closest to the watershed (520; fig. A1.1) and a coefficient of variation of 0.67 as found from analysis of the Guthrie, Oklahoma data (fig. A1.2). Precipitation was initially assigned by subwatershed by selecting a raingage within or near each subwatershed as shown in table A3.2. Due to the similarities in distributional assignments from station to station and subwatershed to subwatershed, a single distribution was assigned for the entire watershed in the interest of computational efficiency (table A3.2).

Knowledge Uncertainty

As discussed previously, 13 parameters were found to be important in determining output uncertainty and treated as probabilistic inputs for Chapter 4 simulations. The parameters and their distributional assignments are shown in table 4.2. Note that there were actually 17 parameters considered since the area of manured pasture was assigned probabilistically by subwatershed. The other parameters were not assigned by subwatershed since they were based on literature values and no additional data were available to allow for changing estimates by subwatershed.

Deterministic Input

The remainder of the parameters were considered constants (deterministic) for Chapter 4 simulations. These inputs were assigned based on estimates made for a previous deterministic modeling effort (Hession et al., 1995). The parameters that vary by subwatershed (K and LS) were determined within the GIS as area-weighted averages within each subwatershed, by each land use. The remainder of the parameters were assigned by land use regardless of the subwatershed in question. Point source information was computed by subwatershed based on the location of the treatment plants. The assigned parameter estimates are given in table A3.3 and A3.4 for nonpoint source and point source related data, respectively. Note that only phosphorus-related inputs are provided since nitrogen was not included in the analysis.

NUMBER OF ITERATIONS

The precision determination curves for the subwatershed-based simulation are shown in figures A3.3 and A3.4 for knowledge uncertainty and stochastic variability, respectively. Sample sizes of 200 and 50 were assumed to provide adequate precision and numerical stability for the analysis performed in Chapter 4.

ADDITIONAL OUTPUT: REDUCTION IN UNCERTAINTY?

The simulations performed with EUTROMOD for Chapter 4 involved a level of discretization (5 subwatersheds). The simulated chlorophyll *a* concentrations and annual total phosphorus loads from Chapter 2 and 4 are compared in figure A3.5 and A3.6, respectively. The study performed in Chapter 3 showed that output variance could be reduced merely by the act of discretization. In addition, based on the Chapter 3 results and addition investigations performed in Appendix 2, we might expect the output uncertainty (in terms of confidence intervals) to be $\sqrt{1/5}$ or (0.45) multiplied by the undiscretized uncertainty or confidence interval.

The stochastic variability of estimated chlorophyll *a* concentrations were reduced significantly from Chapter 2 to Chapter 4 simulations (fig. A3.5). The stochastic variability is represented by a single CCDF; in this case, inspection of the 50th percentile CCDFs indicates that the 90% confidence interval was reduced from a range of more than 2.5 μg/l to just over 1 μg/l. However, the reduction in knowledge uncertainty, represented by the range in the distribution of CCDFS, was reduced from approximately 3.5 μg/l to 3.0 μg/l. This was estimated by inspection of the median values for the 5th and 95th percentile values, before (Chapter 2) and after (Chapter 4) discretization. Inspection of figure A3.6 indicates that the stochastic variability of the total phosphorus estimates actually increased slightly from Chapter 2 to 4. However, knowledge uncertainty, again estimated by inspecting the median values of the 90% confidence intervals, was reduced from approximately 170 Mg/ha to 110 Mg/ha

The results of this analysis were not as straight forward as those performed in

Chapter 3 using the USLE plot. Following are some reasons why the results did not indicate a reduction in output uncertainty of exactly related to $\sqrt{1/5}$:

1. The discretizations (subwatersheds) were not of equal areas as were those in Chapter 3.
2. The parameter values were changed from subwatershed to subwatershed unlike the sub-units for the USLE plot where the parameter distributions were kept constant from sub-unit to sub-unit.
3. Only 17 parameters were considered probabilistic versus 66 in Chapter 2. Even though comparisons made in Appendix 1 suggested that the reduction in input parameters considered uncertain had little effect on output uncertainty, uncertainty was reduced.
4. The subwatershed-based simulations in Chapter 4 required that more parameter estimates be made. Therefore, more error may have been infused into the model due to the "Information Paradox."
5. Some parameters were correlated at 1.0 from basin to basin while others were not correlated at all.

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Table A3.1 Important input parameters contributing to prediction uncertainty.

Importance Rank*	Significant** Input Parameters	Rank-Order Correlation Coefficient by Output: Chlorophyll a	Total Phosphorus Load
1	RC[forest]	-0.67	0.03
2	LFPDIS[manured pasture]	0.47	0.59
3	AREA[manured pasture]	0.31	0.39
4	RC[manured pasture]	0.13	0.29
5	ENP	0.22	0.26
6	C[past]	0.18	0.26
7	LDEPTH	-0.18	0.05
8	LFPDIS[past]	0.15	0.24
9	TF[LS]	-0.15	-0.25
10	TF[FM]	-0.14	-0.29
11	TF[BF]	-0.11	-0.29
12	TF[PR]	-0.10	-0.19
13	TF[HC]	-0.03	-0.19

* Ranked based on absolute value of the rank-order correlation to chlorophyll *a* output.
** Significance based on t-test (n=225, p=2); correlations > 0.13 significant at α =0.05 for either chlorophyll *a* or total phosphorus load output.

Table A3.2 Precipitation station assignments by subwatershed.

Subwatershed	Station Assignment	Distribution
Poteau River	Waldron	Lognormal(120,0.25)*
Fourche Maline Creek	Fanshawe	Lognormal(121,0.25)
Black Fork Creek	Zoe	Lognormal(122,0.24)
Holson Creek	Zoe	Lognormal(122,0.24)
Lake Side	Heavener	Lognormal(121,0.25)
Whole Watershed	(combined)**	Lognormal(121,0.25)

* Lognormal(mean, coefficient of variation).

** Assigned subjectively to entire watershed due to similarities in the distributions by subwatershed.

Table A3.3 Deterministic input parameters related to nonpoint sources.

Subwatershed	Land Use	RC	K	LS	C	P	LFPDIS	LFPSED
Poteau River	Cropland	0.40	0.38	0.6	0.2550	1.0	0.550	300
	Pasture	0.35	0.38	0.6	*	1.0	*	300
	Manured Pasture	*	0.38	0.6	0.0275	1.0	*	800
	Forest	*	0.28	2.1	0.0006	1.0	0.009	300
	Urban/Built-up	0.70	*n/a*	*n/a*	*n/a*	*n/a*	0.250	*n/a*
	Disturbed	0.60	0.32	0.7	0.9800	1.0	0.045	250
	Wetlands/Water	1.00	0.00	0.0	0.0000	0.00	0.000	0
Fourche Maline Creek	Cropland	0.40	0.36	0.9	0.2550	1.0	0.550	300
	Pasture	0.35	0.36	0.9	*	1.0	*	300
	Manured Pasture	*	0.36	0.9	0.0275	1.0	*	800
	Forest	*	0.27	2.8	0.0006	1.0	0.009	300
	Urban/Built-up	0.70	*n/a*	*n/a*	*n/a*	*n/a*	0.250	*n/a*
	Disturbed	0.60	0.34	0.6	0.9800	1.0	0.045	250
	Wetlands/Water	1.00	0.00	0.0	0.0000	0.00	0.000	0
Black Fork Creek	Cropland	0.40	0.36	1.4	0.2550	1.0	0.550	300
	Pasture	0.35	0.36	1.4	*	1.0	*	300
	Manured Pasture	*	0.36	1.4	0.0275	1.0	*	800
	Forest	*	0.25	3.0	0.0006	1.0	0.009	300
	Urban/Built-up	0.70	*n/a*	*n/a*	*n/a*	*n/a*	0.250	*n/a*
	Disturbed	0.60	0.29	0.6	0.9800	1.0	0.045	250
	Wetlands/Water	1.00	0.00	0.0	0.0000	0.00	0.000	0
Holson Creek	Cropland	0.40	0.34	1.1	0.2550	1.0	0.550	300
	Pasture	0.35	0.34	1.1	*	1.0	*	300
	Manured Pasture	*	0.34	1.1	0.0275	1.0	*	800
	Forest	*	0.26	2.6	0.0006	1.0	0.009	300
	Urban/Built-up	0.70	*n/a*	*n/a*	*n/a*	*n/a*	0.250	*n/a*
	Disturbed	0.60	0.29	0.6	0.9800	1.0	0.045	250
	Wetlands/Water	1.00	0.00	0.0	0.0000	0.00	0.000	0
Lake Side	Cropland	0.40	0.37	1.1	0.2550	1.0	0.550	300
	Pasture	0.35	0.37	1.1	*	1.0	*	300
	Manured Pasture	*	0.37	1.1	0.0275	1.0	*	800
	Forest	*	0.28	2.4	0.0006	1.0	0.009	300
	Urban/Built-up	0.70	*n/a*	*n/a*	*n/a*	*n/a*	0.250	*n/a*
	Disturbed	0.60	0.27	1.6	0.9800	1.0	0.045	250
	Wetlands/Water	1.00	0.00	0.0	0.0000	0.00	0.000	0

* Parameter treated probabilistically (knowledge uncertainty); see Table 4.2 for distributional details.

Table A3.4 Point source inputs by subwatershed.

Subwatershed	Waste Flow (MGD)	Phosphorus Concentration (mg/l)
Poteau River	1.11	7.7
Fourche Maline Creek	0.49	7.0
Black Fork Creek	0.02	7.0
Holson Creek	0.00	0.0
Lake Side	0.00	0.0

Note: Only phosphorus inputs were modeled.

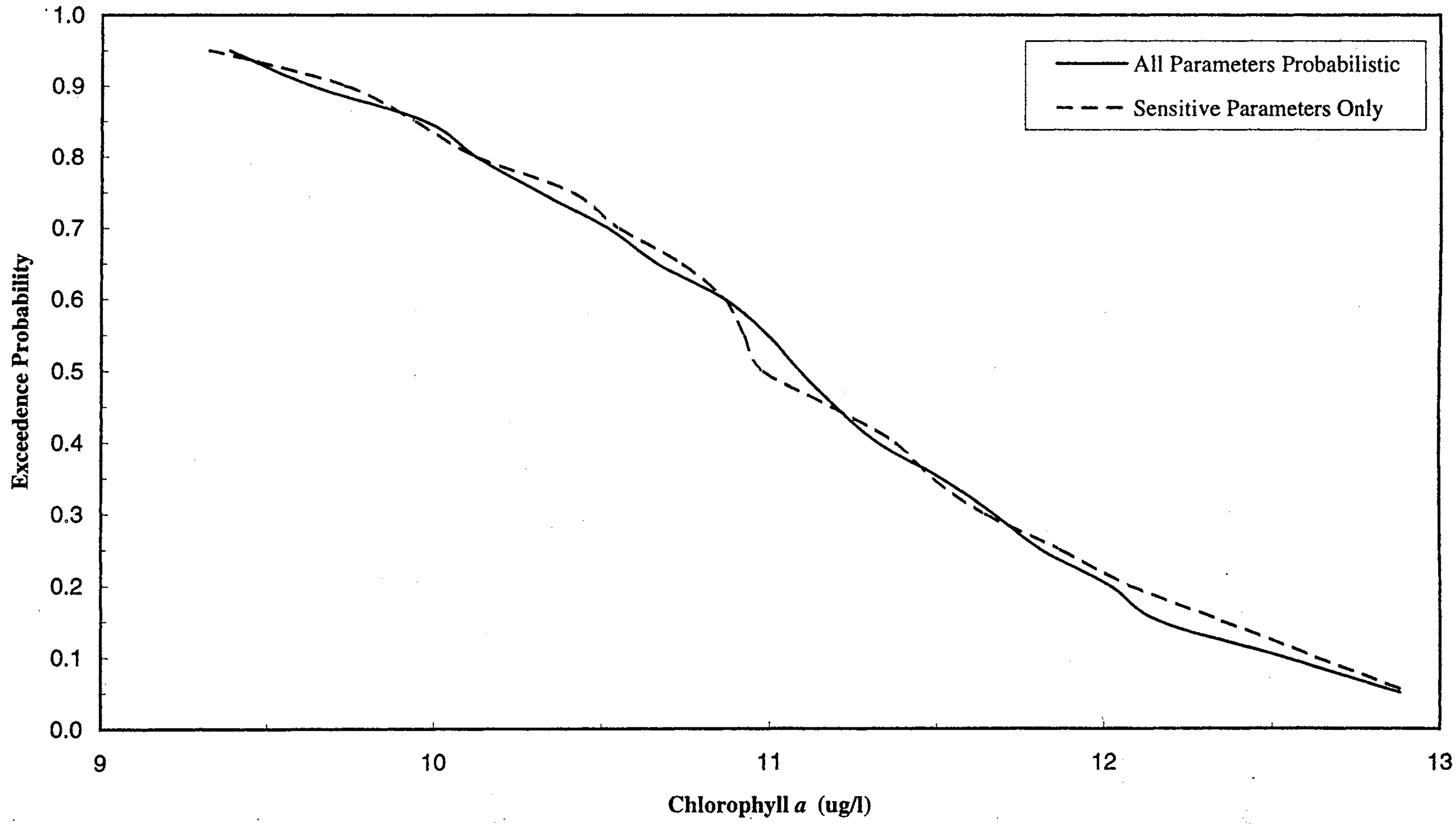

Figure A3.1 Comparing chlorophyll *a* CCDF obtained with all parameters defined as probabilistic inputs to that with only the most sensitive parameters varied (knowledge parameters only, 225 iterations).

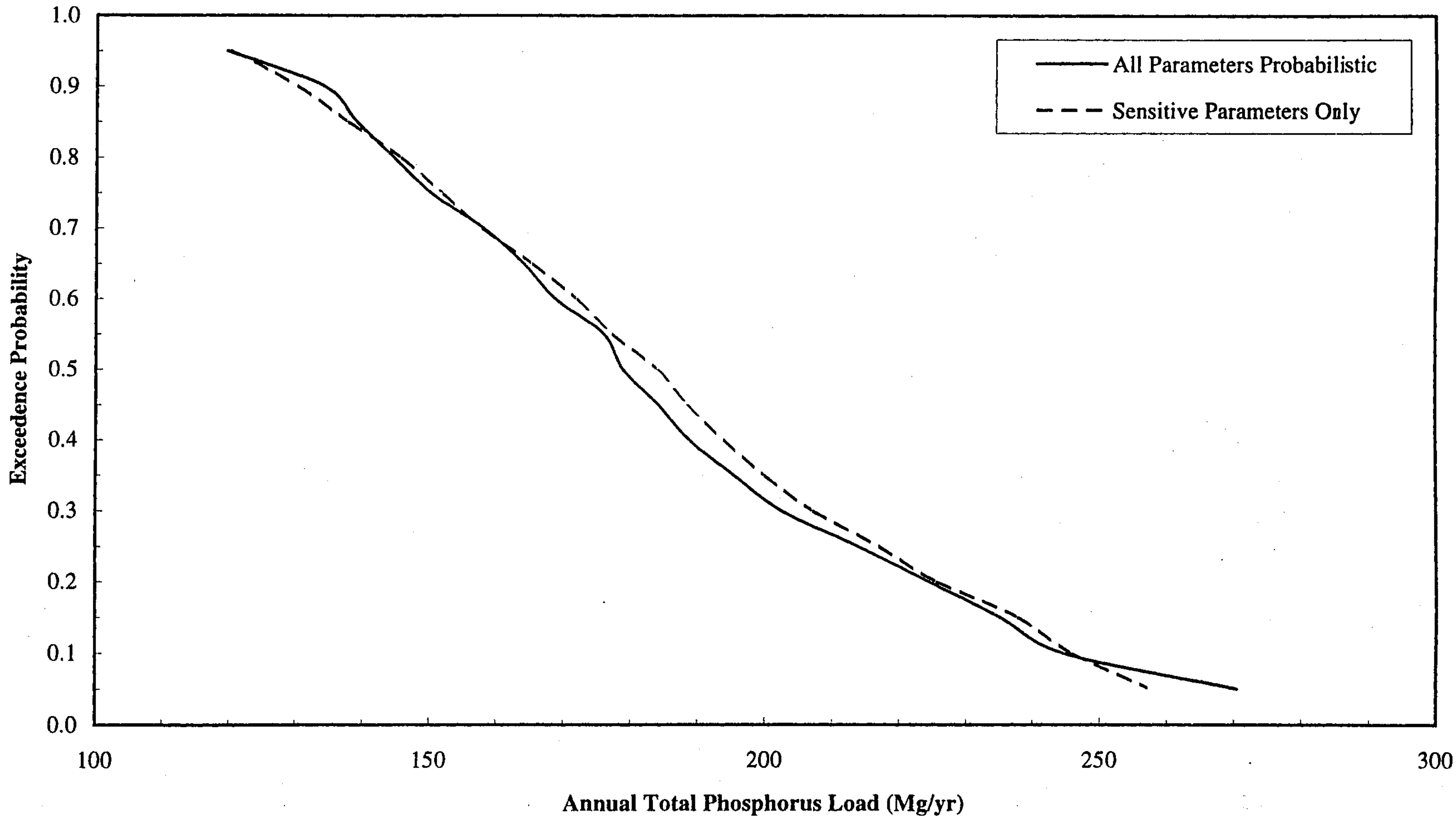

Figure A3.2 Comparing total phosphorus load CCDF obtained with all parameters defined as probabilistic inputs to that with only the most sensitive parameters varied (knowledge parameters only, 225 iterations).

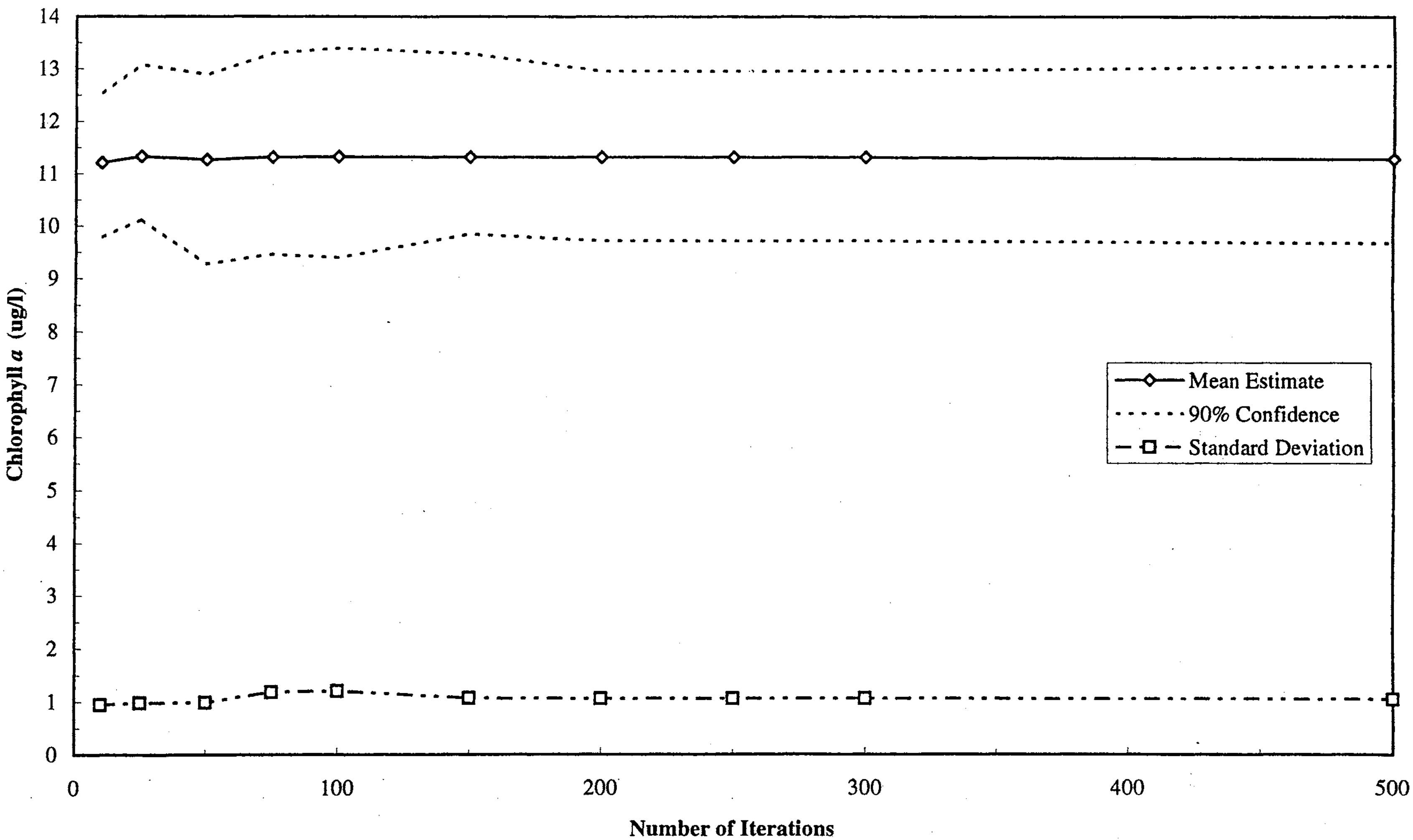

Figure A3.3 Precision determination curves for knowledge uncertainty (200 selected).

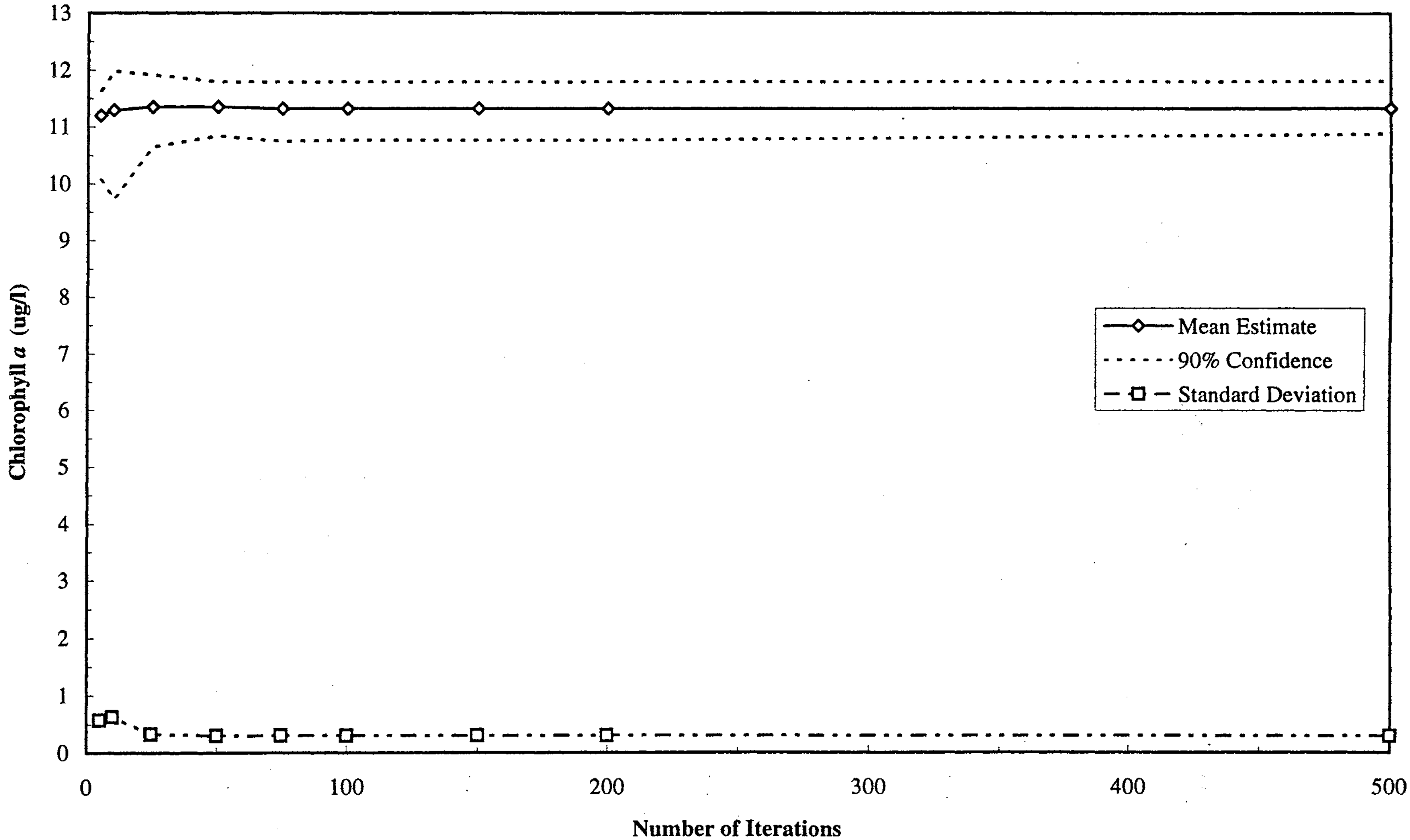

Figure A3.4 Precision determination curves for stochastic variability (50 selected).

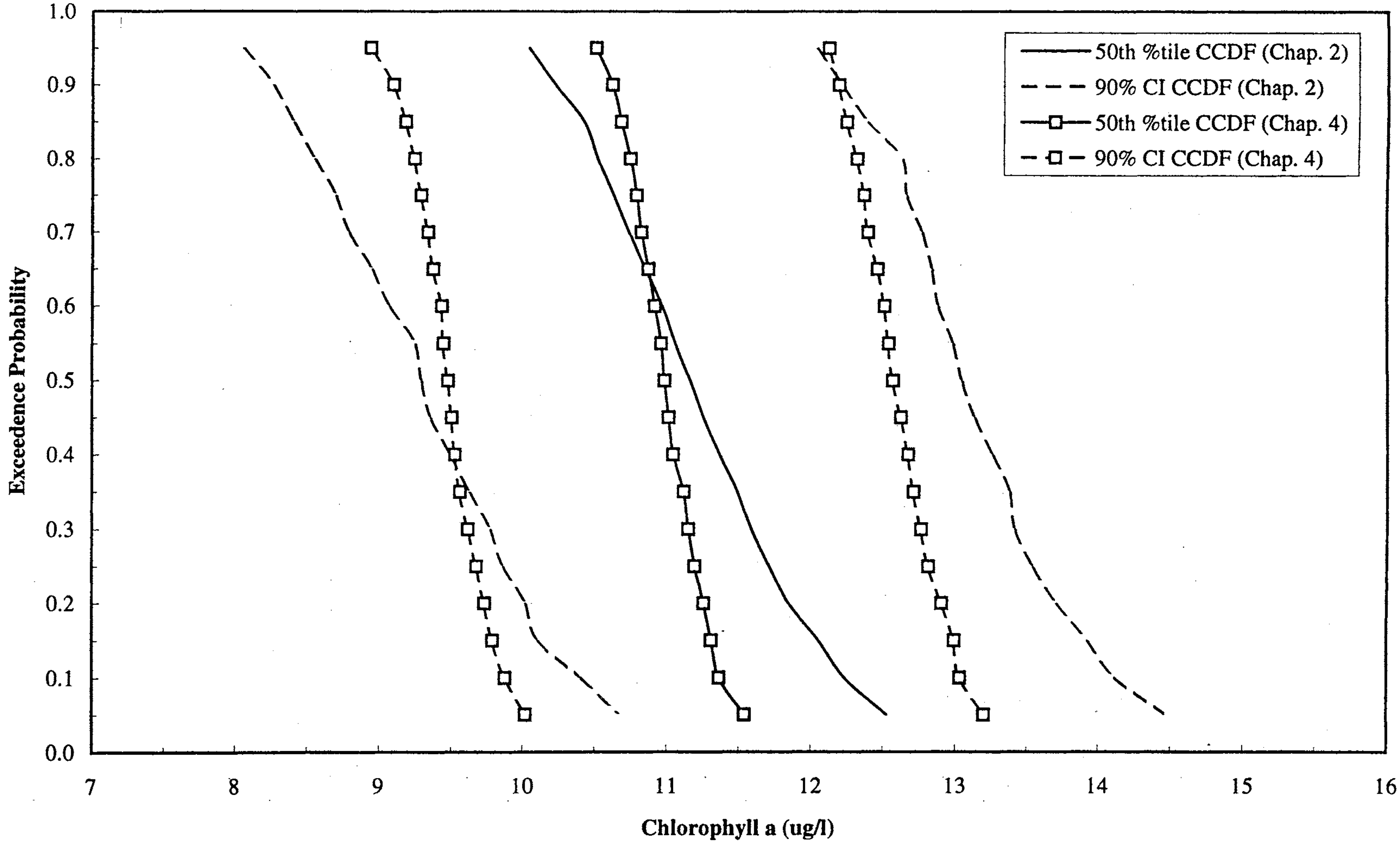

Figure A3.5 Comparing chlorophyll *a* uncertainty from Chapter 2 and 4 simulations.

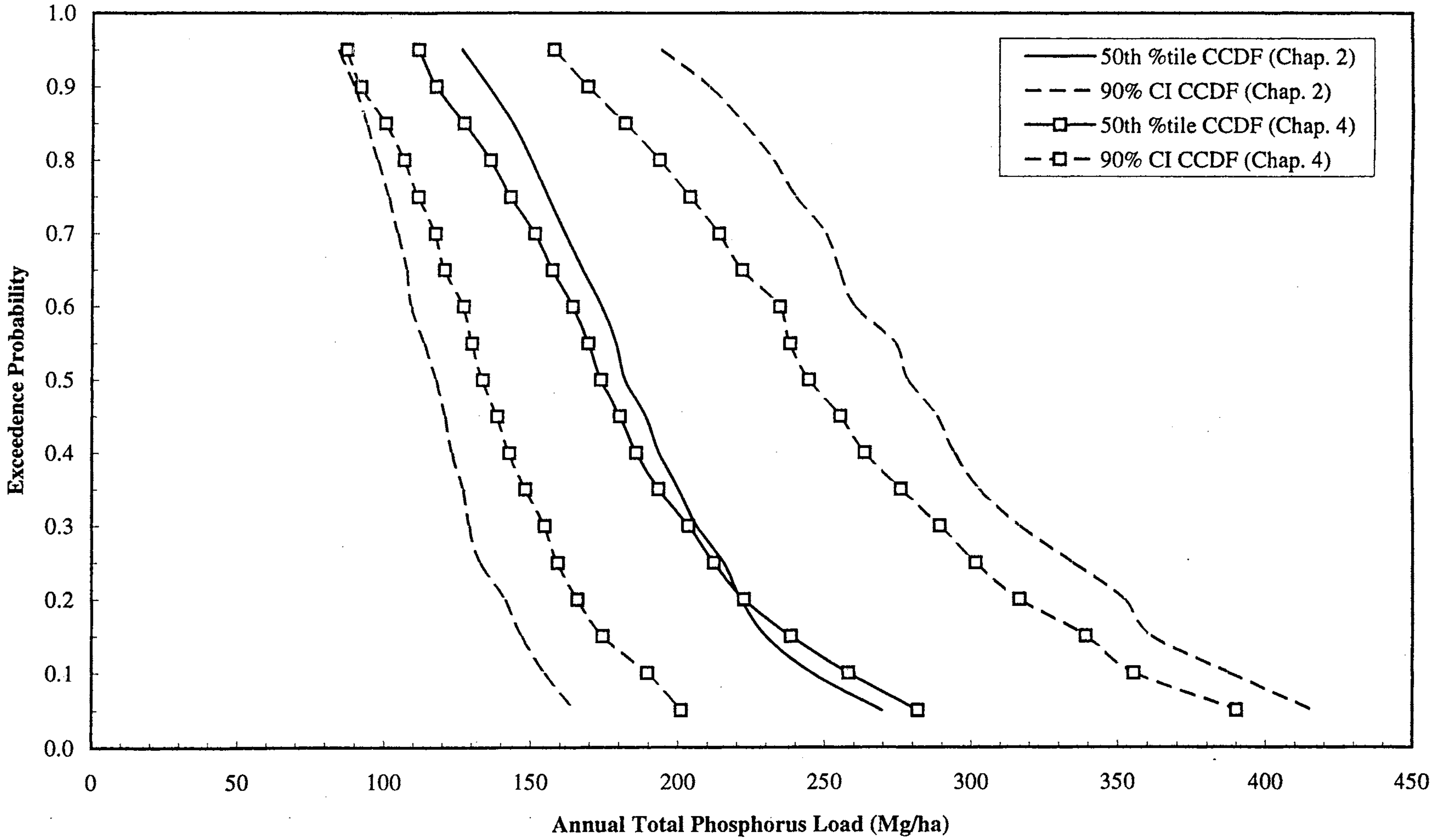

Figure A3.6 Comparing total phosphorus loading uncertainty from Chapter 2 and 4 simulations.

2

VITA

William Culliton Hession

Candidate for the Degree of

Doctor of Philosophy

Dissertation: A WATERSHED-LEVEL ECOLOGICAL RISK ASSESSMENT METHODOLOGY

Major Field: Biosystems Engineering

Biographical:

Personal Data: Born in Baltimore, Maryland, on August 21, 1961, the son of William Joseph, Jr. and Fay Bissell.

Education: Graduated from Bowie High School, Bowie, Maryland in May 1979; received Bachelor of Science and Master of Science degrees in Agricultural Engineering from Virginia Polytechnic Institute and State University, Blacksburg, Virginia in December 1984 and June 1988, respectively; received Doctor of Philosophy degree in Biosystems Engineering from Oklahoma State University in December 1995.

Experience: Graduate Research Assistant, Biological Systems Engineering, Virginia Polytechnic Institute and State University (September 1985 to November 1986); Assistant Scientist, USDA-ARS, Morris, Minnesota (December 1986 to February 1989); Senior Environmental Engineer, Division of Soil and Water Conservation, Richmond, Virginia (February 1989 to March 1992); Research Engineer, Biosystems and Agricultural Engineering, Oklahoma State University (May 1992 to August 1992); Water Resources Presidential Fellow, Biosystems and Agricultural Engineering, Oklahoma State University (August 1992 to present).

Professional Memberships: American Society of Agricultural Engineers, Alpha Epsilon, Soil and Water Conservation Society, American Society of Civil Engineers, American Institute of Hydrology, American Water Resources Association, North American Lake Management Society.