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Addressing Uncertainty in TMDLS: Short Course at Arkansas Water Resources Center 2001 Annual Conference

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Arkansas Water Resources Center

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SECTION 1

Background on the Clean Water Act

History and Implementation of the Clean Water Act

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Introduction

Management of a critical natural resource like water requires information on the status of that resource. The US Environmental Protection Agency (EPA) reported in the 1998 *National Water Quality Inventory* that more than 291,000 miles of assessed rivers and streams and 5 million acres of lakes do not meet State water quality standards. This inventory represents a compilation of State assessments of 840,000 miles of rivers and 17.4 million acres of lakes; a 22 percent increase in river miles and 4 percent increase in lake acres over their 1996 reports.[1]

Siltation, bacteria, nutrients and metals were the leading pollutants of impaired waters, according to EPA. The sources of these pollutants were presumed to be runoff from agricultural lands and urban areas. EPA suggests that the majority of Americans—over 218 million—live within ten miles of a polluted waterbody.[2] This seems to contradict the recent proclamations of the success of the Clean Water Act, the Nation's water pollution control law. EPA also claims that, while water quality is still threatened in the US, the amount of water safe for fishing and swimming has doubled since 1972, and that the number of people served by sewage treatment plants has more than doubled.[3]

It is important to understand that the reports of water quality status are based on *assessed* waterbodies, and do not represent the status of the 3.6 million miles of rivers and streams, 41.6 million acres of lakes, reservoirs, and ponds, 90,500 square miles of estuaries, or 66,645 miles of ocean shoreline. In fact, only 23 percent of the Nation's rivers and streams, 42 percent of lake area, 32 percent of estuary area, and 5 percent of ocean shoreline were assessed.[4] Clearly this survey of water quality is inadequate for characterizing the status of a critical natural resource; the data are not complete.

In spite of the limited data available on water quality, water quality management and protection in the US are changing in ways that may directly or indirectly affect every property owner and business in the country. A series of Federal Court rulings have resulted in the development and implementation of a watershed-based approach to water quality management, the so-called Total Maximum Daily Load (TMDL) approach. The implications of this shift in approach are difficult to grasp without some knowledge of the history of water quality legislation and its implementation. We will provide a brief overview of the Clean Water Act, its history and implementation strategies, in order to provide context for understanding the implications of TMDLs.

The Clean Water Act

More than a hundred years of State and Federal regulations and negotiations have culminated in the Clean Water Act (CWA)[5], a 1977 amendment to the Federal Water Pollution Control Act of 1972. The

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[1] National Water Quality Inventory: 1998 Report to Congress. (EPA 841-R-00-001) United States Environmental Protection Agency Office of Water (4503F), Washington, DC 20460 June 2000
[2] Water Quality Conditions in the United States: A Profile from the 1998 National Water Quality Inventory Report to Congress EPA-841-F-00-006 United States Environmental Protection Agency Office of Water (4503F), Washington, DC 20460 June 2000
[3] *ibid.*
[4] *ibid.*
[5] 33 U.S.C. s/s 1251 et seq. (1977)

CWA was developed as Congress' mechanism for regulating discharges of pollutants to waters of the United States. It gave EPA the authority to set effluent standards on an industry basis (technology-based) and continued the requirements to set water quality standards for all contaminants in surface waters. The CWA makes it unlawful for any person to discharge any pollutant from a point source into navigable waters unless a permit is obtained under the Act. While EPA has oversight responsibilities, the CWA provides for the delegation of many permitting, administrative, and enforcement aspects of the law to state governments[6]. The objective of the CWA is "to restore and maintain the chemical, physical, and biological integrity of the Nation's waters."[7]

The CWA has three explicit goals –

1. The discharges of pollutants into the navigable waters will be eliminated by 1985 (zero discharge goal);
2. Wherever attainable, an interim goal of water quality which provides for the protection and propagation of fish, shellfish, and wildlife and provides for recreation in and on water be achieved by 1983 (fishable and swimmable goal);
3. The discharge of toxic pollutants in toxic amounts is prohibited (no toxics in toxic amounts goal).

The CWA has evolved to include a series of provisions to address specific facets of water quality regulation. The specific provisions of the CWA are often referred to by their US Code of Federal Regulations section number.[8] The CWA is organized into six titles addressing specific components of water quality regulation (Table 1).

Table 1: The Clean Water Act Organization by Title and Section[9]
Title I – Research and Related Programs
Title II – Grants for Construction of Treatment Works
Title III – Standards and Enforcement
• Section 301 Effluent Limitations
• Section 302 Water Quality-Related Effluent Limitations
• Section 303 Water Quality Standards and Implementation Plans
• Section 304 Information and Guidelines (Effluent)
• Section 305 Water Quality Inventory
• Section 307 Toxic and Pretreatment Effluent Standards
Title IV – Permits and Licenses
• Section 402 National Pollutant Discharge Elimination System (NPDES) Permits
• Section 405 Disposal of Sewage Sludge
Title V – General Provisions
• Section 510 State Authority
• Section 518 Indian Tribes
Title VI – State Water Pollution Control Revolving Funds

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[6] 47 states now have delegated authority to administer the CWA.
[7] 33 U.S.C. s/s 1251 et seq. (1977)
[8] The Code of Federal Regulations (CFR) is a codification of the rules published in the Federal Register by the Executive departments and agencies of the Federal Government. The codified rules in the CFR are not law – laws are published as United States Code (USC). However, when promulgated, they carry the weight of law. The CFR is divided into 50 titles, which represent broad areas subject to Federal regulation. Environmental regulations are contained mainly in CFR Title 40: Protection of Environment. Each volume of the CFR is revised once each calendar year. Title 40 is issued every July 1. Sections and subsections are labeled numerically then alphabetically. For example, 40 CFR Section 303 Subsection (d) is generally referred to as subsection 303(d).
[9] From the U.S. EPA NPDES Permit Writers' Manual; December, 1996; EPA-833-B-96-003. Office of Water, U.S. Environmental Protection Agency, Washington, D.C.

HISTORY OF THE CWA

The conflict between two fundamentally different regulatory philosophies is central to the history of the CWA.[10] One philosophy views water pollution in absolute, even moral, terms; the other counts it as a cost balanced against the social benefits of economic activities. One asserts that the goal of regulation is clean water; the other holds that a legitimate use of water is the assimilation of wastes. One proposes federal intervention in what it deems a national problem; the other feels local communities are the most qualified to determine the best uses for their water and, given those uses, how much pollution water bodies can tolerate.[11]

These conflicting philosophies inspired two distinct regulatory strategies: Effluent limitations and water quality standards. Effluent limitations propose to control pollution at the source. Discharges into waters are flatly forbidden unless authorized under a federal permit program. Water quality standards, largely written and enforced by the states,[12] define how much of a pollutant a body or segment of water may contain. These strategies are not mutually exclusive and, in fact, implementation of the CWA as we know it today is a combination of both.

The original legislation, the Federal Water Pollution Control Act of 1948, (PL 80-845), did nothing in the way of establishing federal goals or strategies. It acknowledged the rights and responsibilities of states in matters of water quality and provided funding to states for technical assistance and research.[13] The U.S. Surgeon General was authorized to investigate problems in interstate waters, but federal intrusion faced substantial hurdles. The U.S. Attorney General could bring suit, but only with the approval of the state in which the discharge originated and then only after the Surgeon General had given notice twice to both the state and to the discharger and conducted a public hearing.[14]

The Act was amended five times prior to a major overhaul in 1972. For the most part, these amendments addressed technical assistance and funding.[15] In 1956 a proposal to allow the Surgeon General to establish federal water quality standards failed on the grounds that it would usurp state authority. Besides, it was pointed out in debates, many of the states used water quality standards already.[16] Instead, the states' role in enforcement was enhanced by a 1956 law, (PL 84-660), which encouraged state and interstate abatement measures.[17]

Water quality standards did become law with the 1965 Water Quality Act, (PL 89-234), which required states to submit for federal review interstate water standards and plans for implementation and enforcement. In setting standards, states could consider the various uses for public waters, including recreation and the propagation of fish and wildlife, as well as agricultural and industrial uses.[18] Recognizing waste assimilation as a legitimate use for some public waterways, Congress rejected proposals for a national policy of keeping waters as clean as possible. It also declined, for the time being, to establish federal effluent limitations.[19] The House was uncomfortable with a provision in the Act which authorized the federal government to set standards if a state failed to do so. Arguing that federal

[10] William H. Rodgers, Jr., *Environmental Law*, Second Edition, West Publishing, 1994, p.259
[11] Oliver A. Houck, *The Clean Water Act TMDL Program: Law, Policy, and Implementation*, Environmental Law Institute, 1999, p.11
[12] Rodgers, 342
[13] *The Clean Water Act Desk Reference*, Water Environment Federation, 1997, p.1
[14] WEF, 3
[15] Houck, 13
[16] Houck, 13
[17] WEF, 5
[18] Rodgers, 253
[19] Houck, 13

standards would impair local innovation and lead to Federal zoning, the House argued in vain that sanctions should be limited to withholding funds from states that fail to submit standards.[20]

By 1972 nearly all states had gained approval for water quality standards. The requirement for implementation and enforcement plans, however, went largely unfulfilled, and Congressional reports questioned the adequacy of existing programs as early as 1968.[21] Effluent standards gained credence as Congressional interest turned to resurrecting the Rivers and Harbors Appropriations Act, or Refuse Act of 1899, which flatly prohibited the discharge of any refuse into the nation's navigable waters. In 1970 President Nixon issued Executive Order No. 11574 directing the U. S. Army Corps of Engineers to implement a permit program to enforce the Refuse Act against industrial dischargers.[22]

Congress bristled at this affront to its policy setting authority and moved to write new legislation. Water quality standards were clearly out of favor among Senators, and effluent limitations were in. The House worked to combine the two methods, preserve the states' authority, and limit federal jurisdiction to interstate waters. The House argued as well that any legislation should take into account its costs as well as its benefits. The House also called for a "dynamic approach" and advocated periodic evaluations and studies to enlighten any subsequent legislation.[23]

As far as the Senate was concerned, water quality standards had failed. Furthermore, the cost of implementation should not be born by the government. The Senate favored a "technology forcing" strategy. Set strict effluent standards and deadlines for compliance, argued the Senate, and dischargers will find it in their own economic best interest to install cost-effective treatment systems.[24]

What emerged was a radical change from earlier legislation. The Federal Water Pollution Control Act Amendments of 1972 introduced a Federal permit program giving dischargers until July of 1977 to comply with EPA effluent standards. The legislation also forced technology standards on dischargers, requiring them to install the "best available technology economically achievable" by 1983.[25] 1983 was also the deadline for an interim water quality goal. The ultimate goal, which carried a 1985 deadline, was the elimination of pollution discharges into "navigable waters." The House kept water quality standards in force, but only as a back up in case technology standards failed to bring water up to quality goals. The Senate bill's principal author, Edmund Muskie, went so far as to direct the EPA administrator to assign secondary priority to water quality standards.[26]

In 1976 the National Commission on Water Quality convened to determine the consequences (economic and environmental, among others) of meeting the 1983 goals. Since the commission's composition included five House members and five Senators, the arguments of 1972 were largely revisited. The Commission's chairman, Vice President Nelson Rockefeller, had argued as governor of New York for water quality standards and greater state authority prior to passage of the 1972 Amendments. Over the objections of Senator Muskie, the Commission recommended a new goal to stress "conservation and reuse" rather than zero discharge, and the postponement of some technology requirements. Nevertheless, the 1977 Amendments made only small modifications to technology standards and kept the 1983 and 1985 deadlines intact.[27]

The 1985 "zero discharge" deadline came and went; yet the language remains intact in the Act. The Water Quality Act of 1987 was written in part to address some of the perceived failings of technology standards. Congress revisited water quality standards to tackle "toxic hotspots" that persisted despite technology controls.[28] State implementation and enforcement also made a comeback in addressing such

[20] Houck, 13
[21] WEF, 7
[22] Rodgers, 254
[23] WEF, 9
[24] WEF, 9
[25] WEF, 15
[26] Houck, 24
[27] WEF, 30, 31; Houck 25, 26
[28] Rodgers, 261

"nonpoint" sources of pollution as agriculture, logging, and construction. Thus the tension between Federal and State authority in setting water quality goals continues in implementing the CWA some 27 years after its inception.

IMPLEMENTATION OF THE CLEAN WATER ACT'S WATER QUALITY PROGRAM

The tool for managing water quality under the CWA has been the National Pollutant Discharge Elimination System (NPDES) permit. The Clean Water Act requires any point source[29] wastewater dischargers to have an NPDES permit establishing pollution limits and specifying monitoring and reporting requirements. NPDES permits regulate point sources from municipal wastewater treatment plants, industrial point sources and concentrated animal feeding operations that discharge into other wastewater collection systems, or that discharge directly into receiving waters. Over 200,000 NPDES permits have been issued nationwide, each with five-year renewal cycles.[30] NPDES facilities are classified as either Major (discharge more than one million gallons per day) or Minor (discharge less than one million gallons per day). Discharge limits for NPDES permits are based either on industry specific effluent limitations or waterbody-specific water quality standards. When and if regulated facilities fail to comply with the provisions of their permits, they may be subject to enforcement actions. EPA uses a variety of techniques to monitor permittees' compliance status, including on-site inspections and review of data submitted by permittees.

Effluent Limitations

Technology-based effluent limitations for industrial and municipal discharges are derived from National effluent limitation guidelines (ELGs) developed by EPA, or by applying Best Professional Judgment (BPJ) on a case-by-case basis, in the absence of ELGs.[31] State or Federal EPA NPDES permit writers must determine the appropriate effluent limitation for a type or class of pollutant based on technical and water quality factors. Industrial ELGs are developed based on general industrial categories such as Steam Electric Power Plants, Steel Manufacturing Facilities, and Industrial Laundries. Permits for new industry categories require development of New Source Performance Standards (NSPSs) to set state-of-the-art treatment technology standards for wastewater. Because this is such an expensive process, retrofits of technology in existing plants are generally given more leeway in adaptation of effluent limitations.

By legislation, EPA is responsible for developing ELGs. However, EPA was unable to meet these responsibilities in the first decade of the CWA, resulting in a lawsuit by environmental groups.[32] EPA agreed in a settlement, the terms of which were subsequently incorporated into the 1977 amendments to the CWA, to develop pretreatment standards for a list of priority pollutants and classes of pollutants for 21 major industries (primary industries). The list of priority pollutants now includes more than 150 chemical compounds (predominantly man-made organic and inorganic toxicants), and ELGs have been developed for more than 50 industrial categories.

Water Quality Standards

Water quality standards (WQSs) are rules designed to establish numerical and narrative goals for water quality throughout a State. They provide a basis for states to implement and attain water quality goals. Typical state regulatory language describes water quality standards as "sufficient to protect the ways that water bodies in the state will be used, with defined measurements that will assure water quality is adequate to maintain those uses, and include a margin of safety so that conditions at or just less than the

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[29] The term "point source" means any discernible, confined and discrete conveyance, such as a pipe, ditch, channel, tunnel, conduit, discrete fissure, or container. It also includes vessels or other floating craft from which pollutants are or may be discharged. By law, the term "point source" also includes concentrated animal feeding operations, but not agricultural storm water discharges and return flows from irrigated agriculture.

[30] U.S. EPA NPDES Permit Writers' Manual; U.S. Environmental Protection Agency, Office of Water, December, 1996; EPA-833-B-96-003,

[31] *ibid.*

[32] NRDC v. Costle, March 1979

standards indicate a potential for use impairment prior to that impairment actually occurring."[33] Put more clearly, WQSs are designed to insure waterbodies meet the uses States have decided are appropriate.

Under the Clean Water Act, States and Tribes have the primary responsibility for developing and implementing water quality standards. They must review their standards at least once every three years and submit the results to EPA for its review. EPA determines whether the standards submitted meet the requirements of the CWA and then approves or disapproves them. If disapproved, the State or Tribe must revise the standards to meet EPA's objection or the EPA will propose substitute Federal standards immediately and promulgate final standards within 90 days.

Water quality standards are composed of three parts:
1. Designated Uses
2. Water Quality Criteria
3. Antidegradation Principle

Designated uses and associated water quality criteria are developed by state water quality agencies working with federal regional EPA offices. The water quality criteria provide numeric and narrative standards upon which NPDES permits are based.

Designated Uses

Designated uses have been assigned to every water body in each State at a resolution of the eight-digit hydrologic unit code (HUC).[34] These water bodies are evaluated based on a brief assessment of historic and current use, with a comment period for public input. There are four general categories for water quality use:
1. Aquatic Life Use – Designed to protect aquatic species by establishing optimal conditions for the support of aquatic life and defining indicators used to measure whether these conditions are met.
2. Contact Recreation – Designed to reduce the relative risk of intake of bacteria (especially fecal coliforms), viruses, or toxicants by swimming or other water sports involving direct contact the water.
3. Public Water Supply – Developed to protect a waterbody for use as a source for a public water supply system using only conventional surface water treatment. These regulations are further defined in the Federal Drinking Water Regulations under the Federal Drinking Water Act, and by state Drinking Water Standards.
4. Fish Consumption – Designed to protect the public from consuming fish or shellfish that may be contaminated by pollutants in the water by identifying levels at which certain toxic substances dissolved in water pose a significant risk of bioaccumulation in the tissues of aquatic species.

Waterbodies are often assigned more than one designated use. The most protective designated uses are contact recreation and public water supply. The CWA Section 101(a)(2) establishes as a national goal that, "wherever attainable, an interim goal of water quality which provides for the protection and propagation of fish, shellfish, and wildlife and provides for recreation in and on the water be achieved by July 1, 1983."[35] EPA's position is that if a waterbody has any potential for primary contact recreation it must comply with Use 3 criteria.[36] States must document those waterbodies that are not fishable and/or swimmable, and perform a use attainability analysis (UAA) to determine if they could be.[37] EPA recognizes that some waterbodies are unlikely to be used for swimming, but encourages States to designate primary contact recreation uses for all waterbodies with the potential to support primary contact recreation.

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[33] TNRCC Memorandum of Agreement with EPA Region VI, 1999. Implementation of the TPDES Program. TNRCC, Austin, TX

[34] Watersheds are designated by the number of digits in their USGS Hydrologic Unit Code (HUC) designation; eight-digit HUCs are drainage areas about 1,000 square miles in size, though this is strongly dependent on location.

[35] This is commonly referred to as the "fishable – swimmable goal.

[36] 48 FR 51401 and the Water Quality Standards Handbook

[37] 40 CFR 131.10(j)

Water Quality Criteria
Water quality criteria are assigned to each water body based on designated use. NPDES permit criteria are calculated based on cumulative load to the stream and permit-specific limits for toxics and other pollutants. The difference between the WQS approach and effluent standards is this explicit requirement for consideration of cumulative impacts on the receiving waterbody. EPA is required to publish and update ambient water quality criteria for specific pollutants to "accurately reflect the latest scientific knowledge . . . on the kind and extent of all identifiable effects on health and welfare including, but not limited to, plankton, fish, shellfish, wildlife, plant life . . . which may be expected from the presence of pollutants in any body of water . . ."[38] These water quality criteria are based on scientific judgment using experimental observations on the relationship between pollutant concentrations and environmental and human health effects. States that do not adopt these criteria must demonstrate alternative criteria using similar rigorous analytical processes. This approach is rarely affordable, and thus is not common.

Antidegradation Principle
Water quality criteria are intended to protect designated uses while not allowing water quality to be degraded from ambient conditions. This provision is integrated throughout the NPDES permitting process. Permits cannot be written in such a way as to allow a waterbody's quality to be degraded from ambient conditions, even if they are well above or below the quality necessary to protect their designated uses.

Reconciling Effluent Limitations with Water Quality Standards and the Antidegradation Principle
NPDES permit writers must prepare wastewater discharge permits in such a way as to consider effluent limitations, water quality standards, and the antidegradation principle. In theory, limits are calculated for each pollutant constituent or class using each method. The most restrictive (or protective) value is selected for permitting. However, these processes are time-consuming and expensive. Many permits are prepared using a "boilerplate" approach, applying generic criteria from other permits.

WATER QUALITY REPORTING

The CWA Section 303(d) specifies that States must identify waters that are not attaining water quality standards and submit a list to EPA of those impaired waters. These lists are then used to prioritize state restoration activities. States and other jurisdictions have been required to submit biennial water quality reports to the EPA under Section 305(b) of the Clean Water Act.[39] The agency then compiles the data for a report to Congress; *The National Water Quality Inventory*.[40] In an attempt to standardize the listing process, EPA has recently developed a national Consolidated Assessment and Listing Methodology (CALM). The objective of CALM is to "provide explicit guidance" to States on assessment of attainment/non-attainment of state water quality standards, especially listing/de-listing processes. The CALM program will also "provide explicit guidance" for State activities such as comprehensive state monitoring coverage; presentation of data; causes and sources of impairment; and reporting discrete types of pollutants such as pathogens, nutrients, sedimentation, and fish advisories.[41] States are now required to provide this information every four years rather than two.

CHANGES IN IMPLEMENTING THE CWA

The CWA Section 303(d) also specifies that States must develop Total Maximum Daily Loads (TMDLs) or other watershed approaches for restoring them to compliance. TMDLs are calculations of the amount of a pollutant that a waterbody can receive and still meet water quality standards, or the sum of all allowable

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[38] Section 304(a) of the Clean Water Act, 33 U.S.C. 1314(a)(1)
[39] Consolidate Assessment and Listing Methodology Fact Sheet EPA 841-F-00-004 United States Environmental Protection Agency Office of Water (4503F) Washington, DC May 2000
[40] This report is often referred to as the "305(b) Report."
[41] Water Quality Conditions in the United States: A Profile from the 1998 National Water Quality Inventory Report to Congress. United States Environmental Protection Agency Office of Water (4503F), Washington, DC 20460 EPA-841-F-00-006 June 2000

loads of a single pollutant from all contributing point and nonpoint sources. It includes reductions needed to meet water quality standards and allocates those reductions among sources in the watershed.[42]
The language of the CWA is very explicit:

> *Each State shall establish for the waters identified in paragraph (1)(A) of this subsection, and in accordance with the priority ranking, the total maximum daily load, for those pollutants which the Administrator identifies under section 1314(a)(2) of this title as suitable for such calculation. Such load shall be established at a level necessary to implement the applicable water quality standards with seasonal variations and a margin of safety which takes into account any lack of knowledge concerning the relationship between effluent limitations and water quality.*[43]

While the responsibility of implementing TMDLs resides with States, the act makes it clear that the authority for implementing them resides with the EPA as well:

> *If the Administrator approves such identification and load, such State shall incorporate them into its current plan under subsection (e) of this section. If the Administrator disapproves such identification and load, he shall not later than thirty days after the date of such disapproval identify such waters in such State and establish such loads for such waters as he determines necessary to implement the water quality standards applicable to such waters and upon such identification and establishment the State shall incorporate them into its current plan under subsection (e) of this section.*[44]

More than 20 Federal Judges have interpreted this language very conservatively in response to suits brought by environmental organizations against regional EPAs. During the first twenty years of the CWA, there was no negative ramification for listing a waterbody on the 303(d) list. The requirement that listed waterbodies be restored using a *TMDL or other watershed approach* was never enforced. States had no uniform approach to developing 303(d) lists and criteria were so nonspecific that a single report of a fish kill on a river or lake in a two-year period could result in the waterbody being listed. The result was an inflated accounting of noncompliant waterbodies, and somewhat inaccurate analysis of the degree and sources of degradation of the Nation's waters. In fact, The TMDL requirement grew out of a series of Federal Court rulings rather than EPA rulemaking, generating a rapid shift in water quality management strategies. Suddenly, if a waterbody was on the 303(d) list, it mattered.

The EPA has recently promulgated the Final Rule for TMDLs.[45] This rule is the result of a contentious debate and intense negotiations between industry, agriculture, silviculture, USDA, and many other parties. As written, the TMDL rule will shift water quality management in listed waterbodies to water quality standards-based permits integrated with local nonpoint source controls. EPA is also developing numeric criteria for nitrogen and phosphorus in concert with the TMDL process, to be implemented nationally by 2003. These criteria will be developed on an ecoregions basis. The cost for implementing these criteria could be enormous, given the cost of reducing nutrients in waste flows. This article was intended to provide a background for understanding the significance of the changes in EPA's water quality management approach from permit-based effluent limitation guidelines to watershed-based TMDLs. The potential for increased local control through this process is very high, since both nutrient criteria and TMDLs recognize the regional variability of processes that control ambient water quality. However, there is always a strong tendency within Federal and State agencies to paint with a large brush. Local control of these processes is going to be maintained only through local participation and activity as TMDLs are implemented. A more thorough discussion of the new TMDL rule and its implications will be provided in a subsequent article.

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[42] Water Quality Conditions in the United States: A Profile from the 1998 National Water Quality Inventory Report to Congress. United States Environmental Protection Agency Office of Water (4503F), Washington, DC 20460 EPA-841-F-00-006 June 2000
[43] Section 303(d) of the Clean Water Act, 33 U.S.C. 1313(d)(1)
[44] Section 303(d) of the Clean Water Act, 33 U.S.C. 1313(d)(2)
[45] FR 65 (135), pp. 43586-43680. Thursday, July 13, 2000.

SECTION 2

Uncertainty and Risk in TMDL Processes

DEVELOPING A RISK-BASED APPROACH TO TOTAL MAXIMUM DAILY LOADS IN TEXAS

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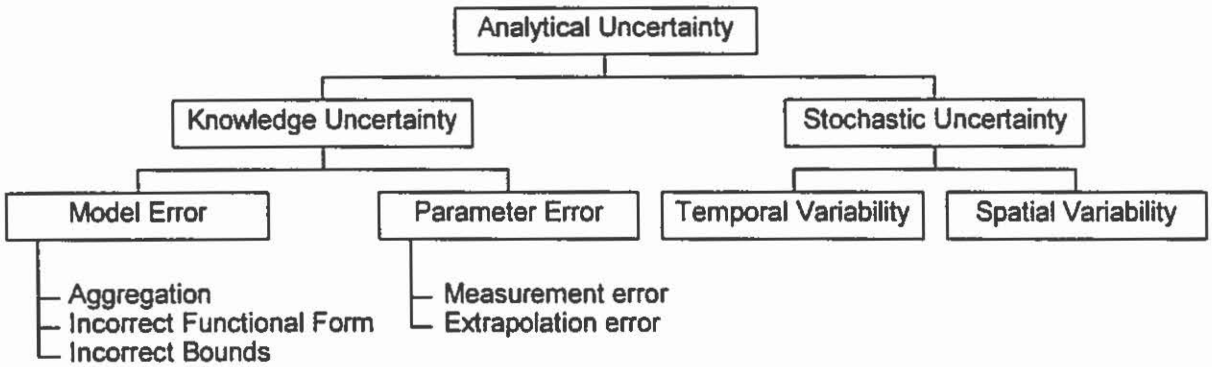
Introduction to Risk Assessment

In most watershed-level assessment and management activities the only thing we are sure of is that we are "in doubt" (Matlock et el., 1994; Hession et al., 1996a, 1996b, 1996c). There are many uncertainties inherent in such activities, including: monitoring/measurement error, model error, model input parameter errors, spatial variability, errors in spatial data layers within a GIS, the effects of aggregation of spatial data when modeling watersheds, and temporal variability. These different errors or uncertainties may or may not be additive. Management of these uncertainties, that is, making decisions in full knowledge of them, is called risk assessment. Management without knowledge of these uncertainties is not competent.

Many types of uncertainties have been identified in the literature utilizing various taxonomic breakdowns (Morgan and Henrion, 1992). Haan (1989), in discussing uncertainty in hydrologic models, classified uncertainty into three categories: the inherent variability in natural processes, model uncertainty, and parameter uncertainty. Similarly, Suter et al. (1987) proposed a taxonomy of uncertainty identifying three sources of analytical uncertainty: 1) errors resulting from our conceptualizations of the world (model error), 2) stochasticity in the natural world, and 3) uncertainties in measuring model parameters (parameter error).

MacIntosh et al. (1994) 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. 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. We have created a taxonomy of uncertainty that combines those defined by MacIntosh et al. (1994), Suter et al. (1987) and Haan (1989) as shown in Figure 1.

Figure 1: Taxonomy of Uncertainty



Sources of Uncertainty in TMDLs

A determination of Total Maximum Daily Load (TMDL) is an analysis used to calculate the maximum pollutant load a waterbody can receive (loading capacity) without violating water quality standards (Hession et al., 1995; Hession et al., 1996b). TMDLs establish waste load allocations (WLAs) for point sources, load allocations (LAs) for non-point sources, background loadings from natural sources, and margins of safety to ensure achievement of water quality goals (EPA, 1991).
The TMDL process has five distinct steps (EPA, 1991):

1. Identify pollutants of concern;
2. Estimate the waterbody's assimilative capacity for those pollutants;
3. Estimate the pollution loading from all sources to the waterbody;
4. Determine the total allowable pollutant load to the water body;
5. Allocate pollutant loading limits to each source, including margins of safety.

There are uncertainties inherent in each of these steps.

We recommend classification and characterization of the uncertainties associated with each component of a TMDL process, and identification of potential mechanisms to reduce these uncertainties. In addition, we recommend that uncertainties be propagated throughout each phase of any modeling analysis utilizing a combination of first-order variance and Monte Carlo simulation methods (Beck, 1987).

Uncertainty and Risk in Modeling

More often than not, hydrologic/water quality model (H/WQ) model simulations are performed using single point estimates for model input variables to predict a single or deterministic output. However, the natural world is uncertain and heterogeneous (Haan, 1995).

The random variability of hydrologic variables and stream flow pollutants has been recognized for centuries (Haan, 1977; Haith, 1987). In addition, parameter values used as input to models are only estimates since the actual values are not known with certainty. The importance of incorporating uncertainty analysis into H/WQ models has been emphasized by many authors (Beck, 1987; Reckhow, 1994; Haan et al., 1995; Kumar and Heatwole, 1995; Hession et al., 1996a, 1996b, 1996c). 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).

Uncertainty is not a desirable aspect of modeling investigations for watershed-level assessment and management. However, uncertainty and stochasticity are ubiquitous in such analyses and must not be ignored. In the past, the incorporation of a quantitative uncertainty analysis into modeling activities required special expertise and computing power. However, the accessibility of powerful personal computers and spreadsheet-based Monte Carlo analysis software make it possible for most assessors and managers to "honestly" incorporate uncertainty analysis into their analyses, thereby allowing for more knowledgeable decision making.

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. Large mechanistic models are too complex 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 complex mechanistic models (Hession et al., 1985).

However, 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.

Data required for simulating basin loadings and stream response include information about climate, watershed characteristics, land use management, and stream morphometry (Reckhow, 1994). Climate parameters include precipitation duration and intensity, temperature, and evaporation estimates. Several parameters are used to describe the watershed; stream morphometry is described using surface area and mean depth. The stream model QUAL2E treats each land use in the simulated watershed as a homogeneous unit. Many of the input parameters are required for each land use and, therefore, the number of input parameters depends on the number of unique land uses simulated. While much of the data necessary for modeling watersheds is available in BASINS, it is at relatively low resolution.

Water Pollution Trading - An Example of Uncertainty at Work

The U.S. Environmental Protection Agency (US-EPA) is promoting the use of watershed nutrient trading for reduction of point and non-point source pollution in response to President Clinton's 1995 program on *Reinventing Environmental Regulation* (EPA, 1996). This market approach to pollution control has received widespread support from economists as a cost-efficient method for promoting environmental protection, and has been relatively successful in reducing lead and sulfur dioxide in pollution of the atmosphere (Dales, 1968; Baumol and Oates, 1975; Taff and Senjem, 1996).

US-EPA policy "encourages trades that will result in desired pollution controls at appropriate locations and scales" (US-EPA, 1996). This approach requires that water quality standards be met throughout the watershed. The benefits of pollution trading include:

- reduced costs of meeting pollution control responsibilities,
- accelerated or increased implementation of pollution control measures at the watershed level,
- expansion of NPS pollution reduction beyond current capabilities,
- increased community understanding and involvement in watershed-level environmental protection, and
- development of novel approaches to pollution control.

The process of trading involves an agreement between parties contributing to water quality problems within the same watershed; this approach offers flexibility to reduce pollutants at the lowest cost for the watershed community. Cost-effective reduction of NPS pollution, especially nutrients, can be achieved through trading between point (often urban or industrial) and non-point (often agricultural) sources. The market approach encourages those dischargers with low-cost abatement options to make reductions from gains in trading with high-cost dischargers.

Uncertainty with Water Pollution Trading. Market-based approaches have been cited in the economics literature as a cost-effective means to improving environmental quality (Dales, 1968; Baumol and Oates, 1975; Hahn and Hester, 1989). However, very few NPS pollution trading schemes have been developed for point or non-point source water pollution control (Hahn, 1989; Taff and Senjem, 1996; US-EPA, 1996). Taff and Senjem (1996) suggest that the substantial institutional uncertainty associated with water pollution trading diminishes the practicality of this tool. Specifically, they identify four classes of uncertainty:

1. Water Quality Uncertainty - NPS pollution is often not well characterized or quantified, while point sources generally are monitored. However, most point sources in Texas do not control or monitor nutrients in their discharge, adding uncertainty.
2. Practice Uncertainty - The effectiveness of best management practices varies greatly from site to site, making predicting this effectiveness difficult.

3. Enforcement Uncertainty - The trading partners may be concerned that if the prescribed NPS pollution reduction is not achieved, the regulatory agency (TNRCC and EPA-Region VI) may issue a violation of the point source's National Pollutant Discharge Elimination System (NPDES) permit, resulting in a substantial fine.
4. Cost and Benefit Uncertainty - The costs and benefits associated with NPS pollution reduction are difficult to quantify. The trading partners may be concerned about equitable compensation.

The successful implementation and performance of a nutrient trading strategy depends in largely on whether regulatory authorities support the proper functioning of a tradable nutrient rights market (Hahn and Noll, 1983; Hahn, 1989; Atkinson and Teitenberg, 1991; Letson, 1992; Crutchfield et al., 1994).

The challenge is to reduce the uncertainty associated with watershed-level pollution trading by quantifying the uncertainty associated with each stage of the TMDL and nutrient trading process and optimizing trading options. Quantifying the uncertainty associated with point to non-point source trading will make the market approach to pollution control more attractive to state and regional water quality regulatory authorities. This may foster increased participation of the regulated community in monitoring watershed contributions of nutrients. Reducing each source of uncertainty associated with nutrient trading will result in increased application of watershed-level pollution trading, a concurrent reduction of nutrient loading to our nation's waters, and reduction in the costs of achieving an acceptable level of environmental quality.

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TWO-PHASE UNCERTAINTY ANALYSIS: AN EXAMPLE USING THE UNIVERSAL SOIL LOSS EQUATION

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ABSTRACT. *Hydrologic and water quality (H/WQ) models are important tools for environmental assessment and management. Model simulations are often performed deterministically, which results in a single estimate of the output while ignoring the natural variability of the modeled system and other knowledge uncertainties. We present a two-phase Monte Carlo method 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 present the methods and to illustrate the value of incorporating uncertainty analysis into modeling investigations. In addition, we demonstrated that, when using Monte Carlo techniques, output variance is reduced as the level of discretization increases in spatially distributed modeling. This reduction is due to the mathematics of the underlying statistics if the parameters of the discrete units are not perfectly correlated across the units. Landscapes are often represented as a collection of discrete subunits in distributed parameter H/WQ models. Therefore, model output uncertainty can be underestimated due to discretization rather than due to increased confidence in parameter estimates or model improvements if the correlation structure among the discrete units is not considered. Additional work is needed to develop and test procedures for determining and using the correlation structure among parameters of the discrete units to accurately present output variability and uncertainty for distributed H/WQ models using Monte Carlo analysis techniques.* ***Keywords.*** *Uncertainty, USLE, Monte Carlo, Risk.*

Hydrologic and water quality (H/WQ) models are important tools for environmental assessment and management. Hydrologic and water quality simulation models are often used as an alternative to or in addition to field observations for analyzing and predicting H/WQ responses to perturbations within a watershed and for developing land management plans. More often than not, model simulations are performed using single point estimates for model input variables to predict a single or deterministic output. However, the natural world is uncertain and heterogenous (Haan, 1995). The random variability of hydrologic variables and stream flow pollutants has been recognized for centuries (Haan, 1977; Haith, 1987). In addition, parameter values used as input to models are only estimates, since the actual values are not known with certainty. The importance of incorporating uncertainty analysis into H/WQ models has been emphasized by many authors (Beck, 1987; Reckhow, 1994; Haan et al., 1995; Kumar and Heatwole, 1995; Hession et al., 1996). 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 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 model parameters is greater than 10 to 20% (Zhang et al., 1993).

Monte Carlo simulation is a method for numerically operating a complex system that has random components (Brown and Barnwell Jr., 1987). Repeated simulations are performed with the model using randomly selected parameter values. At the beginning of each simulation, parameter values are chosen from predetermined 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,

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the validity of Monte Carlo procedures is not affected by nonlinearities or discontinuities in the model (Brown and Barnwell Jr., 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. Monte Carlo techniques are used extensively and have become the preferred method of propagating uncertainty in complex H/WQ modeling investigations (Haan, 1989; Summers et al., 1993; Taskinen et al., 1994; Kumar and Heatwole, 1995; Prabhu, 1995; Haan and Zhang, 1996). There are, however, several drawbacks associated with Monte Carlo techniques. They assume complete representation of the population distribution of the model parameters and are inherently computationally intensive (Zhang et al., 1993).

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. For instance, many H/WQ models are distributed parameter models that assume the physical system is made up of small, uniform, and discrete subunits (Tim, 1995). Each discrete subunit is characterized by a uniform set of properties and input parameters. When performing Monte Carlo procedures on spatially distributed models, do we reduce the output variability simply by subdividing the study area into multiple units?

We present a two-phase Monte Carlo procedure for propagating uncertainty in H/WQ models based on procedures previously used in environmental and ecological risk analyses (Helton, 1994; MacIntosh et al., 1994). In order to illustrate the two-phase Monte Carlo procedure and explore the effects of discretization on output variance we use 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 estimated long-term average annual soil loss per unit area, A, is estimated from:

$$A = R\,K\,LS\,C\,P \qquad (1)$$

where

R = rainfall erosivity factor
K = soil-erodibility factor
LS = dimensionless topographic factor that represents the combined effects of slope length and steepness
C = cover and management factor
P = 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 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 H/WQ 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., 1995). The USLE has also been used 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 evaluate the USLE. Several comprehensive studies have been conducted concerning the accuracy of the USLE (Wischmeier, 1972; Risse et al., 1993). Others have evaluated the USLE under specific conditions in different locations (Onstad et al., 1976; Kramer and Alberts, 1986). 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, 1987; 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 an original USLE test plot in Guthrie, Oklahoma. This plot was chosen for its close proximity to other studies currently being conducted in Oklahoma by the authors. The plot data were used to illustrate the two-phase uncertainty propagation methodology and to compare simulated and measured annual soil loss distributions in order to illustrate the value of incorporating uncertainty analysis into modeling studies. We also illustrated how discretization level can affect output variance in a spatially distributed model when using Monte Carlo techniques.

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 from several of these "control plots" were actually included in the analyses resulting in the empirically based USLE (Wischmeier and Smith, 1978). We selected one of these plots (plot 1-2) which had a long period of record (27 years from 1930 through 1956) for use in our study. The plot was 1.83 m wide × 44.26 m long and had a slope of 7.7%. The plot consisted of a Stephensville fine sandy loam soil planted in cotton. The cotton was harvested in the fall, leaving cotton stalks over winter, and turnplowed parallel to slope (up- and downslope) in the spring.

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 using various taxonomic schemes (Suter et al., 1987; Morgan and Henrion, 1992; Helton, 1994; MacIntosh et al., 1994). We used 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. This uncertainty, which can also be considered subjective uncertainty (Helton, 1994), is a property of the analyst and available data. Stochastic variability is due to random variability of the natural environment and is a property of the natural system. Stochastic variability can be further divided into temporal and spatial variability. The reader is referred to Suter et al. (1987) and Morgan and Henrion (1992) for a more thorough discussion of uncertainty types.

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). When a distinction between stochastic variability and knowledge uncertainty is not maintained, their effects on output uncertainty become commingled, making it difficult to draw useful insight (Helton, 1994). For instance, knowledge uncertainty can be used as an indicator of the potential benefits of additional measurements. Knowledge uncertainty can be reduced by decreasing the possible range of parameter estimates through physical measurements of the appropriate phenomena. However, stochastic variability is a natural property of the system being studied and may be quantified, but normally can not be reduced.

Parameter Uncertainty. We incorporated both knowledge uncertainty and stochastic variability into our analysis. All parameters in the USLE 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 has been found to vary spatially within a given soil type (Bajracharya and Lal, 1992) as well as temporally (Römkens, 1985).

In order to perform Monte Carlo simulations, a probability distribution defining the range of possible values must be assigned for each uncertain parameter. Using the two-phase Monte Carlo methodology, it is possible to assign both stochastic and knowledge uncertainty to individual parameters while separating their effects on model predictions. In fact, in a separate study performed by the authors (Hession et al., 1996), measured values for R were not available. Therefore, knowledge uncertainty was assigned using the range of isoerodent lines shown to be closest to the study area on the isoerodent map of Wischmeier and Smith (1978), thereby quantifying our uncertainty as to which mean value of R to use. The knowledge uncertain values were then used to define the distribution quantifying stochastic variability. However, in the current analysis, we defined annual rainfall erosivity (R) as having only stochastic variability. We did not account for knowledge uncertainty of R, since measured values were available. The measured annual rainfall erosivity values were found to be lognormally distributed using 27 years of measured values for the Guthrie plot (table 1).

The soil erodibility (K) and cropping and management (C) factors were treated as having only knowledge uncertainty representing the range of possible values available from the literature. Stochastic variability was ignored for these parameters since no information was available to quantify the temporal or spatial stochasticity. A uniform distribution was used for both K and C. 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 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 distributions for K and C are shown in table 1.

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 values used for LS and P are presented in table 1.

It is important to include correlations among input parameters during error propagation (Reckhow, 1994). A distribution-free rank correlation methodology (Iman and Conover, 1982) is employed by the software package, described below, used to perform Monte Carlo simulations in this study. Correlation coefficients ranging from −1 to 1 can be assigned subjectively to dependent variable pairs. However, we assumed that the correlation between the different factors in the USLE were negligible. We did, however, incorporate correlations later during our discretization analysis to illustrate their impact on model predictions.

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 by separating knowledge and stochastic uncertainty. The uncertainty analysis was performed using @RISK ver. 3.1a (Palisade Corporation, Newfield, N.Y.) linked with Microsoft Excel ver. 5.0 (Microsoft Corporation, Cambridge, Mass.). 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-

Table 1. Parameter assignments for uncertainty analysis and a deterministic estimate of the USLE in metric units

	Uncertainty Simulations		
USLE Parameter	Uncertainty Type	Distribution or Constant	Deterministic Estimate
R	Stochastic	Lognormal (383,0.76)*	372
K	Knowledge	Uniform (0.21,0.45)†	0.31
LS	Constant	1.13	1.13
C	Knowledge	Uniform (0.42,0.59)	0.59
P	Constant	1.0	1.0

* Lognormal distribution (Mean, Coefficient of Variation).

† Uniform distribution (Minimum, Maximum).

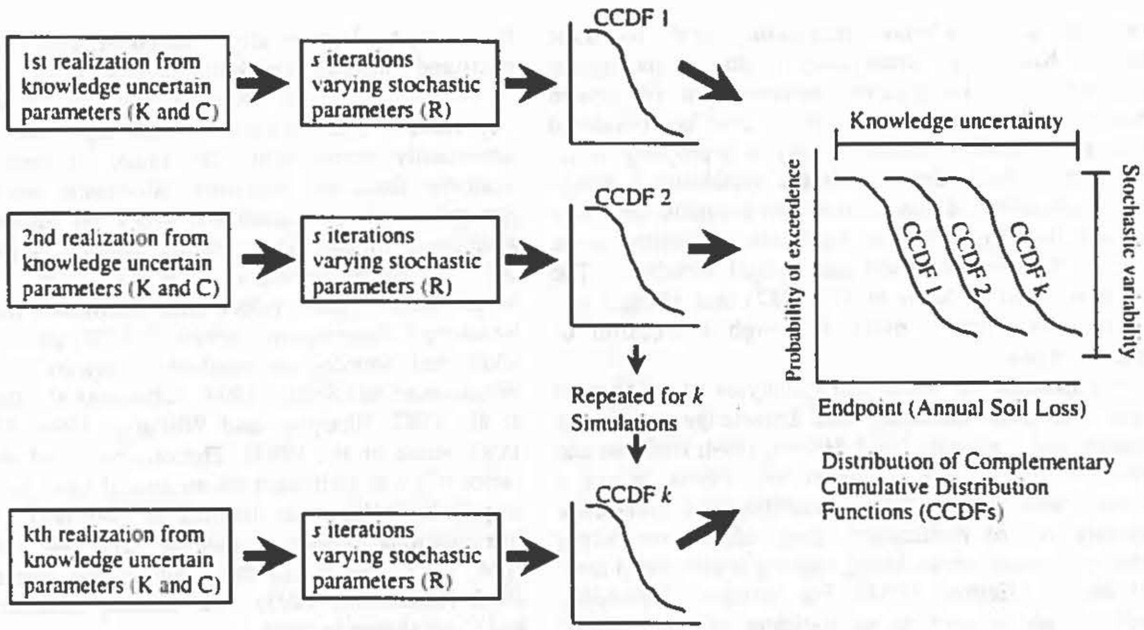


Figure 1–Illustration of two-phase Monte Carlo procedure used to propagate knowledge uncertainty and stochastic variability separately.

phase Monte Carlo procedure illustrated in figure 1. 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, K and C, while each iteration within a simulation represented a unique stochastic parameter, R. Random sampling of the assigned parameter distributions 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). K and C were assumed to be independent of each other.

First, a value was drawn at random from each of the distributions for K and C. Together these random values defined a simulation scenario. Next, a value was drawn at random from the distribution of R, representing stochastic variability. These values of R, K, and C were then used along with the constant parameters (LS and P) as input to the model, whose output represented one iteration of the simulation scenario. Without changing the values of K and C, a new value was drawn at random for R and a new output value was computed. This resampling of R was repeated *s* times, resulting in *s* estimates of output for the simulation scenario. These *s* output results were analyzed statistically, resulting in a complementary cumulative distribution function (CCDF) that defines a probability of exceedence (Helton, 1994). This represents the uncertainty in model results due to the stochastic variability in R for one simulation scenario (K, C pair).

At this point, new values were drawn at random from the distributions of K and C representing a new simulation scenario. Holding these constant, R was again sampled *s* times, resulting in a new CCDF. This entire process was repeated for *k* simulation scenarios. Each iteration resulted in a single estimate of the output. 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 within each CCDF showed the effects of stochastic variability on the model estimates while the distribution of CCDFs showed the effects of knowledge uncertainty.

Discretization Effects

Most H/WQ models are distributed parameter models to some extent. These models rely on discretization of a study area 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 annual soil loss distributions with the USLE from the experimental plot at different levels of discretization as illustrated in figures 2a through 2e. We divided the plot vertically so as not to affect the slope length factor from subunit to sub-unit.

Results and Discussion

Two-phase Monte Carlo Simulation

We applied the two-phase Monte Carlo procedure to the USLE for the experimental plot in Guthrie, Oklahoma. The Monte Carlo procedure was performed using 100 simulations ($k = 100$) with each simulation consisting of

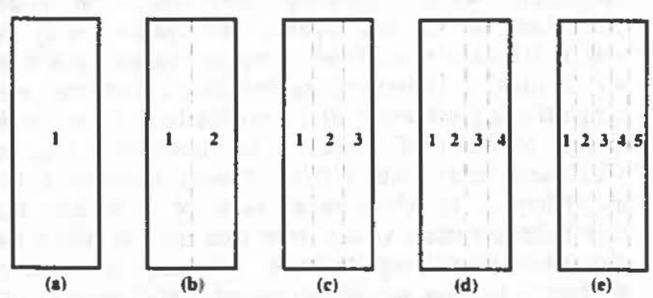
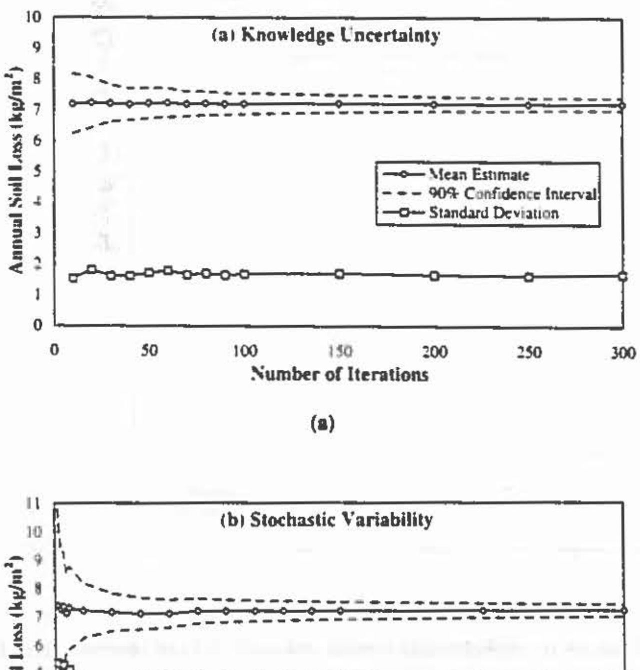


Figure 2–Erosion plot schematic showing five discretization levels used to test the effects of discretization level on output variance.

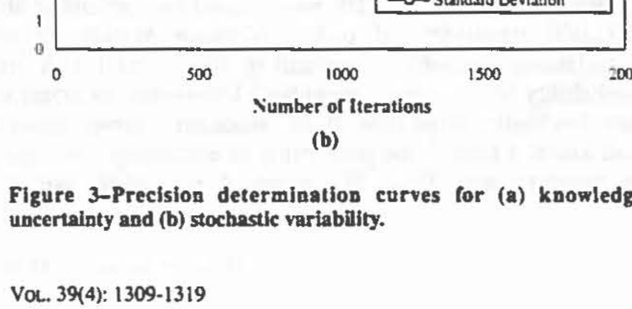
1,000 iterations ($s = 1000$). The sample sizes were determined based on an inspection of figures 3a and 3b showing the means, 90% confidence intervals, and standard deviations versus number of iterations. Figure 3a shows the results of varying only the parameters with knowledge uncertainty (K and C) and figure 3b shows the results of varying only the stochastically varying parameter (R). In these figures, we looked for the mean and standard deviation to stabilize as well as the confidence intervals to become fairly constant. We assumed that 100 samples for knowledge uncertainty and 1,000 for stochastic variability would provide adequate precision and numerical stability for our analysis.

Figure 4 shows the distribution of CCDFs of annual soil loss resulting from 1,000 iterations within 100 simulations. 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 of this information is presented in figure 5, which provides the 5th, 50th, and 95th percentile curves of the distribution of simulated CCDFs.

In figure 5 we present the complementary empirical distribution function (EDF) (Conover, 1980) for the 27 years of observed annual soil loss and the complementary EDF for estimates of annual soil loss from the Guthrie plot conducted by Risse et al. (1993). The estimates of Risse et al. (1993) were computed for each year using the observed annual R



(a)



(b)

Figure 3–Precision determination curves for (a) knowledge uncertainty and (b) stochastic variability.

values and NRCS estimates of K and C. Risse et al. (1993), however, did not present their estimates as distributions, but rather as estimates for given years to be compared one-to-one with the observed annual soil loss for that year.

A visual comparison of the observed EDF of soil loss and our stochastic estimates with 90% confidence intervals indicated that much of the observed EDF fell within our 90% confidence intervals. However, the predicted distribution of CCDFs did not capture the lower and upper tails of the observed distribution of annual soil loss. As expected, our 50th percentile distribution and those of Risse et al. (1993) were very similar in magnitude as well as distributional shape.

In figure 6 we present the relative frequency histogram for the observed annual soil loss and the probability density function (PDF) of simulated annual soil loss developed by combining all 100,000 iterations of our two-phase analysis (1,000 stochastic iterations times 100 knowledge simulation scenarios). The 90% confidence interval for the simulated PDF is also shown in figure 6. In addition, the observed mean annual soil loss 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 (table 1) are shown in figure 6. It is interesting to note that the observed mean and deterministic USLE estimate compared well. The observed mean and USLE deterministic estimate of long-term annual soil loss were within our 90% confidence interval.

The histogram of observed annual soil loss is highly skewed, with many small annual values and a few very extreme outliers. These extreme, low probability observed annual soil losses (the highest being 83 kg/m^2) greatly influenced the mean of the observed annual soil loss. The USLE was developed as an estimate of long-term "average" annual soil loss and it does appear to do a good job of estimating this long-term "average" or mean value. However, this single "average" value contains very little information for use in making detailed management decisions.

A particular management decision does not result in a single environmental response to be realized year after year, but a whole range of responses to which probabilities can be assigned (Haan, 1995). Identifying and understanding the full range of possibilities, as presented stochastically through a quantitative uncertainty analysis, provides more useful information for planning and management. Given a CCDF of annual 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, where risk can be defined as the probability of occurrence of an undesired event (Suter et al., 1987).

As an example, suppose a land manager wishes to reduce the annual soil loss from a field to a predetermined average annual soil loss level. However, the manager is willing to take some risk, but would like to know the probability of exceeding this predetermined level after implementing specific land management practices. This can be accomplished by modifying the range of possible values for the USLE parameters to reflect various management practices (usually using the C and P factors), performing the simulations again with the modified parameter distributions, and presenting the results as a probabilistic summary.

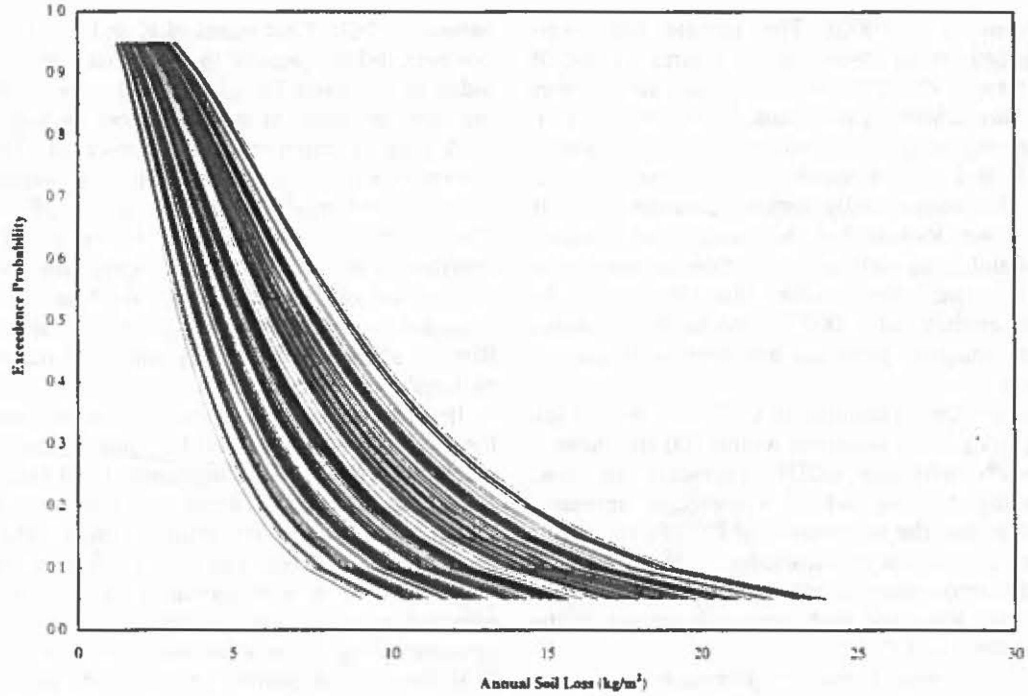


Figure 4–Distribution of CCDFs of simulated annual soil loss for Guthrie, Okla., experimental erosion plot using the USLE.

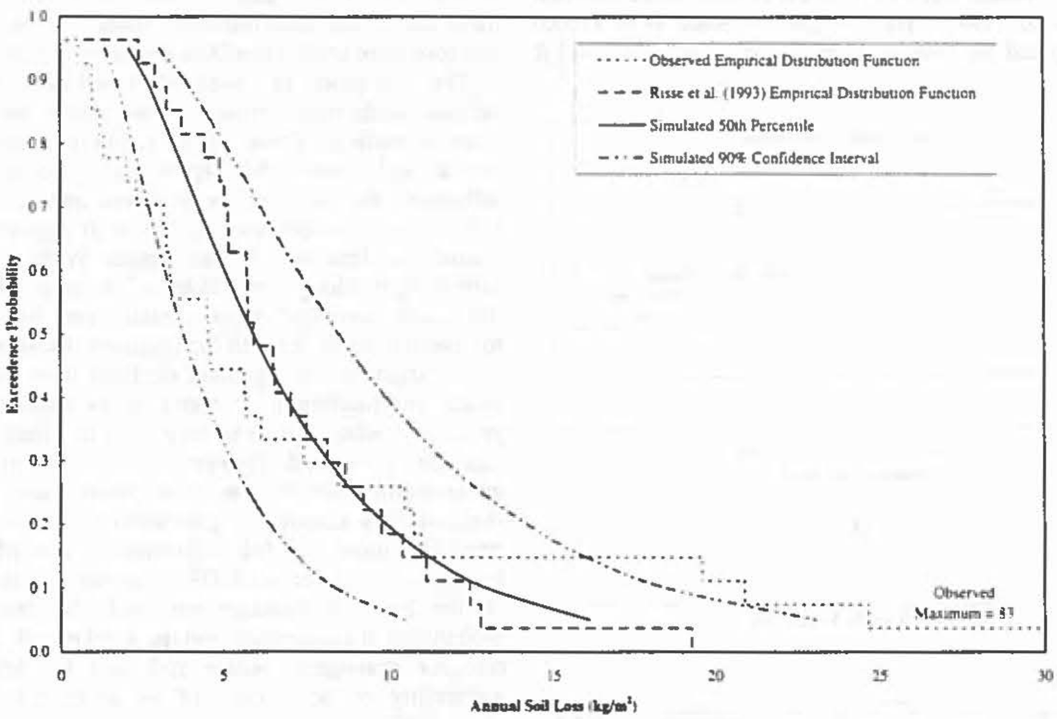


Figure 5–Summary of the distribution of CCDFs of simulated annual soil loss for the experimental erosion plot with EDFs of observed annual soil loss and annual soil loss estimates from Risse et al. (1993).

To illustrate these concepts, we performed the simulations for the experimental plot again, but changed the support practice factor (P) to reflect tillage and planting on the contour. The P factor was assigned to a uniform distribution ranging from 0.5 to 0.6 to reflect the range of values found in the literature (Beasley, 1972; Wischmeier and Smith, 1978) and included as an input parameter with knowledge uncertainty (along with K and C). In figure 7 we present the simulated CCDF resulting from this change in management. This CCDF was created by combining all 100,000 iterations of our two-phase Monte Carlo simulations, thereby representing the overall risk or probability of exceedence from both knowledge uncertainty and stochastic variability. If the manager's target annual soil loss is 4 kg/m^2, the probability of exceeding this value is approximately 35%. This level of risk might not be

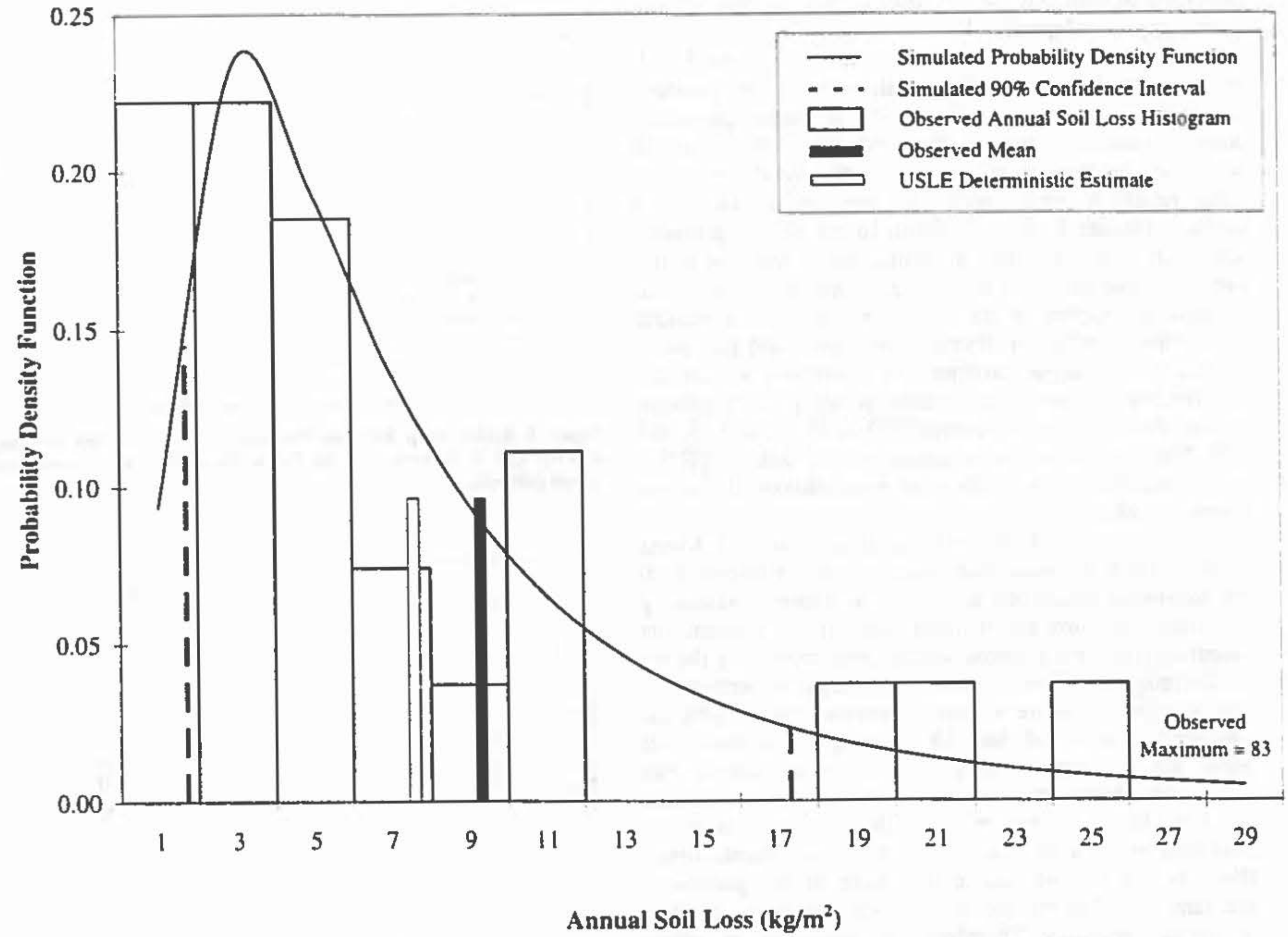


Figure 6–Comparison of the observed annual soil loss histogram and the PDF of simulated annual soil loss with the observed mean annual soil loss value and a deterministic USLE estimate.

acceptable and further simulations would be required to reflect alternative management practices until a given practice provided an acceptable level of risk of exceeding the 4 kg/m^2 annual soil loss target. Such analysis, providing a level of risk for use in the decision-making process, would not be possible using the USLE in a deterministic manner.

The simulated PDF and CCDF presented in figures 6 and 7, respectively, illustrate the utility and flexibility of the two-phase methodology. Knowledge and stochastic uncertainty are propagated separately throughout the analysis. This separation allows for valuable insights such as determining important parameters where additional physical measurements might help reduce the level of knowledge uncertainty and resulting output uncertainty. However, for determining the overall risk of exceeding a given annual soil loss, given the existence of both knowledge uncertainty and stochastic variability, it is informative and less complicated to combine all the stochastic and knowledge iterations from the two-phase Monte Carlo simulations and create a single CCDF.

Effects of Discretization of Uncertainty Propagation

We estimated the annual soil loss for each discretization level in figures 2a through 2e by computing the annual soil loss from each subunit as a mass per unit area (kg/m^2) using the USLE, multiplying these by the area of the subunit to get a mass (kg), and adding these soil losses for the subunits together resulting in an annual soil loss estimate for the entire plot (kg). We varied the K and C factors for

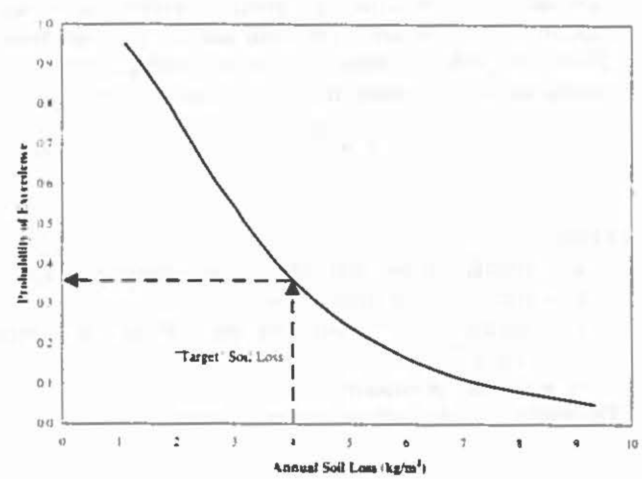


Figure 7–Simulated CCDF of annual soil loss resulting from a change in the support practice factor (P) to reflect tillage and planting on the contour.

100 iterations for each subunit using LHS sampling. It is important to note that the K and C values for each subunit 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 subunits are probably significant. In particular, in this investigation we merely discretized a small, relatively homogeneous plot and the correlation of a single parameter from one subunit 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. 2a through 2e) 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 (Iman and Conover, 1982).

The variances of the estimated annual soil losses resulting from the combined effects of discretization level and parameter correlation are shown in figure 8. Assuming no parameter correlations from subunit to subunit, the output variance was reduced significantly merely by the act of discretization. This reduction in output uncertainty is also apparent in figure 9, which provides the CCDFs for simulated annual soil loss for each discretization level under the assumption of parameter independence (no correlations from subunit to subunit). One might argue that the knowledge 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 uncertainty or spatial variability. Therefore, the reduction in output uncertainty was purely a mathematical artifact, not related to the knowledge of the model user. A more detailed discretization of a landscape 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; however, no reduction in input uncertainty was assumed in this analysis.

The reduction in output variance due to discretization is expected from an inspection of the underlying statistics. Consider the case where parameter correlations between subunits are set to zero. The total annual soil loss from a discretized plot is a linear function of independent random annual soil loss estimates from the subunits, given as:

$$Z = \sum_{i=1}^{m} a_i x_i \tag{2}$$

where

Z = annual soil loss estimate for the entire plot (kg)

a_i = area of the *ith* subunit (m^2)

x_i = annual soil loss per unit area of the *ith* subunit (kg/m^2)

m = number of subunits

The variance is defined as (Devore, 1987):

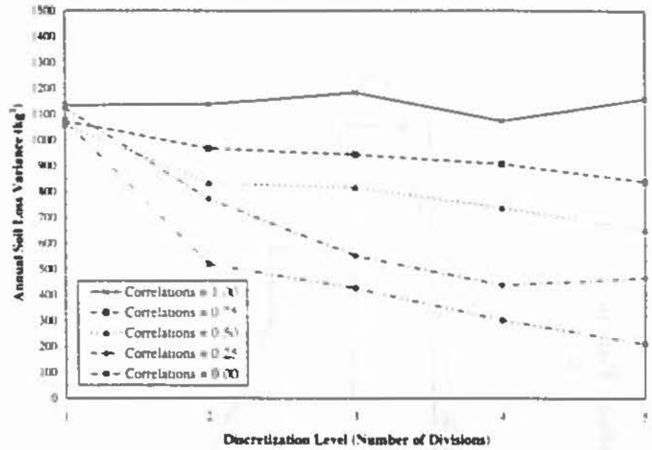


Figure 8–Relationship between simulated annual soil loss variance and the level of discretization for five levels of parameter correlation across subunits.

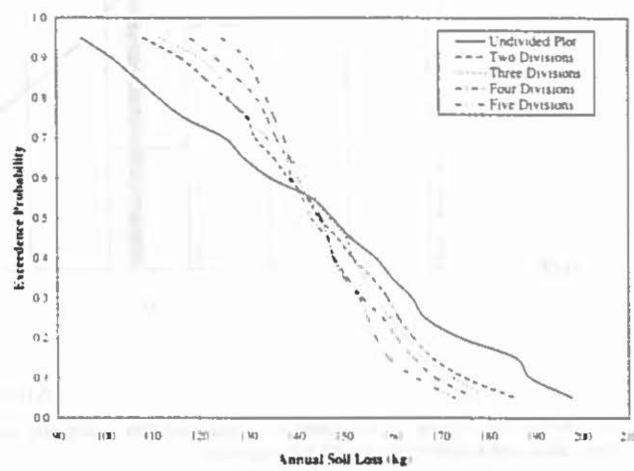


Figure 9–The CCDFs for simulated annual soil loss for each discretization level under the assumption of parameter independence (no correlations from subunit to subunit).

$$\mathrm{Var}(Z) = \sum_{i=1}^{m} a_i^2 \,\mathrm{Var}(x_i) \tag{3}$$

where Var(Z) is the variance of annual soil loss for the entire plot (kg^2) and Var(x_i) is the variance of annual soil loss for the individual subunits (kg^2/m^4). Note that since the variables are independent and random, the covariances are equal to zero. In addition, since the subunits are equal in size, the areas of the *ith* subunits can be redefined as:

$$a_i = \frac{A}{m} \tag{4}$$

where A is the area of the entire plot (m^2). Therefore, the variance of Z becomes:

$$\mathrm{Var}(Z) = \sum_{i=1}^{m} \frac{A^2}{m^2} \,\mathrm{Var}(x_i) \tag{5}$$

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 annual soil loss per unit area were nearly equivalent. Therefore, the variance of Z becomes:

$$\mathrm{Var}(Z) = \frac{A^2}{m^2} m \,\mathrm{Var}(x_i) = \frac{A^2}{m} \mathrm{Var}(x_i) \qquad (6)$$

This mathematical evaluation agrees with the simulation results shown in figure 8. For example, the variance of the soil loss estimate for the plot with five subunits (fig. 2e), where $m = 5$, had a variance approximately one-fifth 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 natural landscape, an inherently 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 8 and 9 illustrate that, unless we assume correlations equal to 1.0 across discretizations, the mere act of discretization results in a reduction in output variance or uncertainty.

Many distributed parameter H/WQ models require the discretization of the field, watershed, or landscape into uniform grids. This can result in thousands of discrete subunits used to represent a single land area. Based on the trend seen in the line representing zero correlations in figure 8, we could expect the output variance to approach zero if we subdivide an area into thousands of discrete units. Does this mean that by simply subdividing an area into many smaller units we can model the hydrology or water quality with near certainty?

Increased correlations tend to mask the effect of discretization level on output variance (fig. 8). What level of correlation is appropriate in distributed parameter H/WQ modeling? Should this correlation be based on the actual spatial correlation structure in the physical system 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 (Warrick and Nielsen, 1980; Peck, 1983; Parkin, 1993).

Additional research is needed to determine the appropriate level of correlation at the field, watershed, or landscape scale for the parameters used in H/WQ models. In addition, a method of correcting for the mathematical reduction in output variance due to discretization needs to be developed so that model results can be presented realistically and honestly. Finally, the reduction in output uncertainty due to discretization will vary from model to model and from output to output depending on the computational schemes involved. In the example above, the reduction in output variance was a result of the annual soil losses from the individual subunits being summed to estimate annual soil loss for the entire plot. In complex H/WQ models, however, the output from the discrete units can be combined mathematically in a variety of different ways to produce estimates for the entire land area under study. Therefore, the reduction in output uncertainty when performing Monte Carlo-type simulations will vary from model to model. More research is needed to evaluate the effects of discretization on output variability for specific H/WQ models.

Summary and Conclusions

We presented a two-phase Monte Carlo methodology that allows for the evaluation and propagation of natural stochastic variability and knowledge uncertainty separately in H/WQ modeling efforts. We illustrated the procedure using the USLE and 27 years of rainfall and erosion data from an experimental plot in Oklahoma. Comparisons between our probabilistic estimates of annual soil loss and the observed distribution of annual soil loss were made. We concluded that a stochastic representation of annual soil loss is more useful for decision making than a single estimate of the mean that is strongly influenced by extreme values. A probabilistic estimate allows for management based on the level of risk acceptable to resource managers.

We also illustrated that under the assumption of independence, model 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 study area into many uniform units resulting in hundreds or even thousands of discrete subunits used to represent a single land area, thereby, greatly reducing output variance. 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. A better understanding of the actual spatial correlation structure in the physical system will be invaluable in addressing this problem.

Uncertainty is not a desirable aspect of H/WQ modeling investigations for environmental assessment and management. However, uncertainty and stochasticity are ubiquitous in such analyses and must not be ignored. In the past, the incorporation of a quantitative uncertainty analysis into modeling activities required special expertise and computing power. However, the accessibility of powerful personal computers and spreadsheet-based Monte Carlo analysis software make it possible for most assessors and managers to "honestly" incorporate uncertainty analysis into their analyses, thereby allowing for more knowledgeable decision making.

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Linking Chemical and Biological Monitoring Components in the TMDL Process

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Abstract

A TMDL for nutrients was initiated for the North Bosque River in central Texas in 1998. Monitoring associated with the TMDL effort has focused on nutrients due to their role in promoting excessive algae growth as indicated by elevated chlorophyll-α levels throughout the river. Because Texas has only narrative nutrient criteria, linkages between in-stream chlorophyll-α and nutrient concentrations were needed to develop quantifiable in-stream nutrient targets that would link these biological and chemical components. The technical challenge was in defining the limiting factor to algal growth and establishing a quantifiable nutrient target that was meaningful and feasible for control implementation. Algal bioassays indicated phosphorus to be the limiting nutrient within the river system. A number of different approaches were used for establishing relationships between phosphorus and chlorophyll-α concentrations for target development. An initial in-stream target of 0.03 mg/L PO_4-P using an annual average of monthly grab samples was proposed to achieve a chlorophyll-α level of about 20 μg/L. This target is being reviewed and a watershed-loading model (SWAT) is being applied to evaluate implications of management practices on the feasibility of meeting the proposed target.

Introduction

Water quality standards for the State of Texas as determined by the Texas Natural Resource Conservation Commission (TNRCC) indicate that the North Bosque River should be suitable for contact recreation, drinking water supply and a healthy aquatic ecosystem (TNRCC, 1996). Water quality assessments show high levels of nutrients contributing to excessive growth of algae within the river, which can impair the river's aesthetic value, potentially causes taste and odor problems in drinking water and result in fish kills under certain conditions

(TNRCC, 1999a). Low dissolved oxygen (DO) levels and elevated bacterial levels are also indicated as water quality concerns along the North Bosque River (TNRCC, 1996). In response to nutrient conditions, classified segments 1226 (North Bosque River) and 1255 (the Upper North Bosque River) are on the Texas 303(d) list for development of Total Maximum Daily Loads (TMDLs). This TMDL process focuses on the control of elevated nutrient levels with the expected benefit of increased DO and decreased bacterial levels. Although Lake Waco (Segment 1225), the receiving waterbody for the North Bosque River, is not currently on the 303(d) list, the stakeholder group is considering the water quality of the entire Lake Waco watershed within the TMDL process.

The North Bosque River is located in the Brazos River Basin as part of the LakeWaco watershed and originates in Erath County northwest of Stephenville (Figure 1). From Stephenville, the river flows from northwest to southeast by the towns of Hico, Iredell, Meridian, Clifton and Valley Mills before entering Lake Waco in McLennan County. The watershed covers about 781,000 acres (316,000 ha) stretching across the Cross Timbers and Prairies ecoregion with a small portion of the southeast end of the watershed occurring in the Blacklands ecoregion (Schuster and Hatch, 1990). The North Bosque River supplies surface water for the cities of Clifton and soon Meridian. While Lake Waco supplies water for the city of Waco and surrounding communities. Over 200,000 people use water originating from the North Bosque River as their primary drinking water source (TNRCC, 1999a). The North Bosque River also provides water for a variety of agricultural activities as well as some recreational opportunities, such as fishing, under normal flow conditions. North Bosque River flows can be quite variable, and the river's upper reaches are often dominated during late summer by municipal wastewater treatment effluent.

The TMDL process as a tool for implementing State water quality standards follows seven general steps (USEPA, 1998a). These include: 1) identifying the problem, 2) identifying the difference between desired and current conditions, 3) identifying the sources of impairment, 4) identifying controls to reduce impairment, 5) implementing controls, 6) monitoring for improvement and 7) revising the TMDL as justified by monitoring after controls are implemented. This paper will focus on target development within the North Bosque River TMDL effort for the control of excessive algae growth associated with accelerated eutrophication. The goal of the target is to sustain biological ecosystem integrity. Specific tasks include determining what limits the growth of algae within this system and developing predictive relationships between the limiting factor and algae production to identify feasible endpoints or targets for control efforts.

Within aquatic systems, eutrophication has multiple meanings. In scientific terms, eutrophication refers to the natural aging process of streams and lakes as sedimentation and loadings occur over time. In terms of evaluating water quality, eutrophication or more specifically cultural eutrophication refers to the human induced increase in the rate of the "aging process" of a lake or stream. When an overabundance of algae occurs in response to cultural eutrophication, a number of different potential impacts can occur. These include changes in the structure and diversity of the aquatic ecosystem with changes in algal populations and communities, periods of oxygen deficiency as respiration demands exceed oxygen production, increases in pH with changes in the carbonate-carbonic acid balance, decreases in water clarity and releases of toxins or other undesirable substances from certain species of algae, such as geosmin from *Oscillatoria chalybea* or MIB (2-methylisoborneol) from *Anabaena circinalis* (Izaguirre, et al., 1982). Some general references on the potential impacts of algal blooms on aquatic ecosystems include Laws (1993), Boyd (1990), Riemann and Søndergaard (1986), and Middlebrooks et al. (1973).

The level of nutrients and plant growth within a waterbody generally defines its trophic status. Categories for tropic state range from oligotrophic, referring to low productivity, to mesotrophic, eutrophic and hypereutrophic, referring to very high productivity. Trophic status is generally measured in units of chlorophyll-α (CHLA) in the water column (mass per unit volume) or on the stream bottom (mass per unit area) as a surrogate for primary productivity. CHLA levels associated with the various trophic state categories have been suggested for lakes (Carlson, 1977 and Wetzel, 1983) and for streams (Dodd et al., 1998; Table 1). The difficult problem in water quality assessment is defining the appropriate trophic state for a given waterbody and the factor or factors that can be controlled to limit the production of algae if a lower trophic status is desired. Some limits to the production of algae include nutrients, primarily nitrogen (N) and phosphorus (P), light availability, water residence time or "wash out", water velocity, substrate factors and grazer abundance. Where cultural eutrophication is a problem,

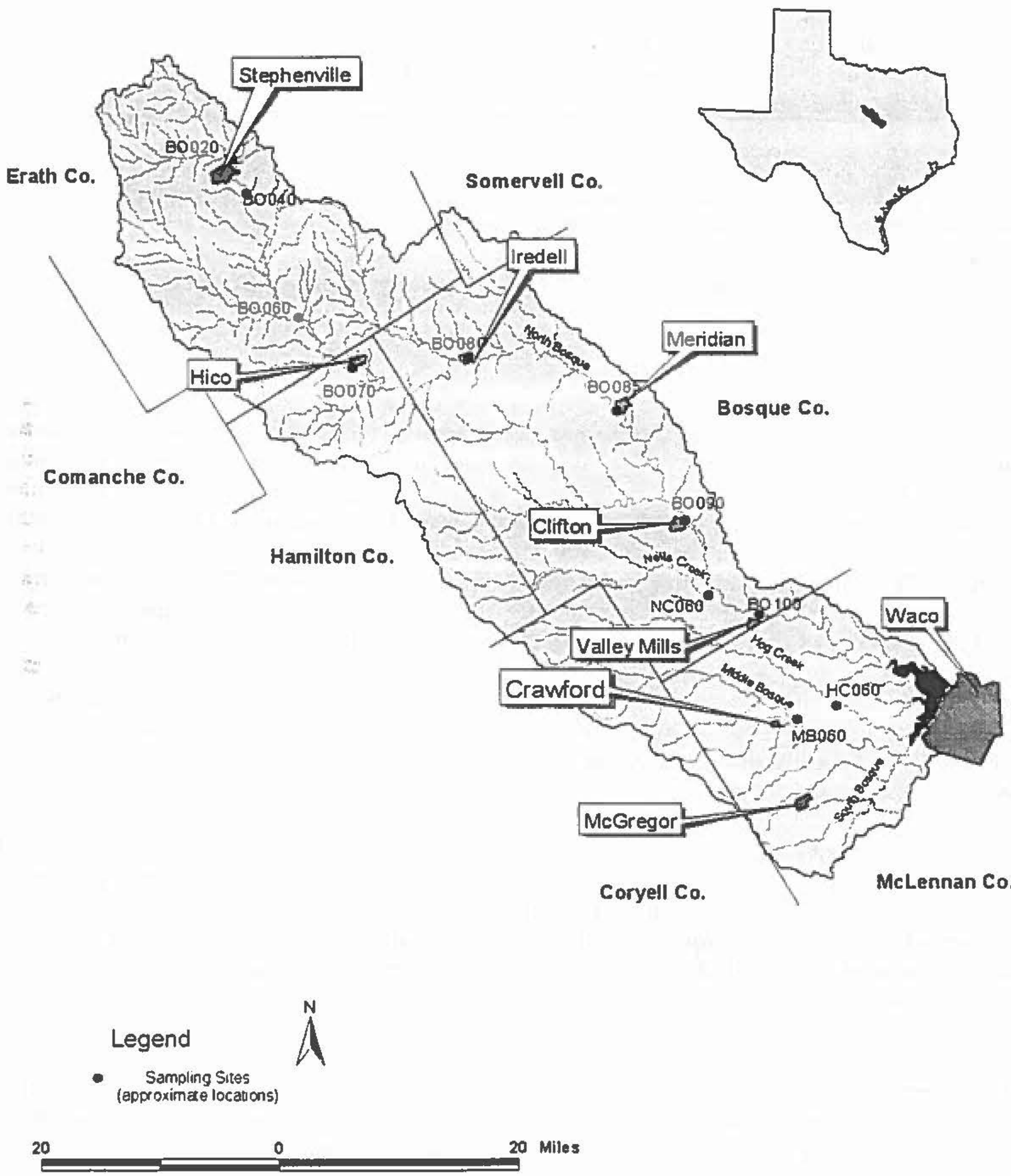

Figure 1. Lake Waco watershed and locations of selected sampling sites.

an overabundance of nutrients is almost always the cause. In freshwater systems, phosphorus is generally the limiting nutrient, while in marine or estuary systems, nitrogen is more often limiting (Gibson, 1997). The limiting nutrient may then indicate the potential factor for controlling eutrophication.

Table 1. Suggested chlorophyll-α concentrations (μg/L) in relation to trophic state of lakes and streams.

Trophic State	Lakes (Carlson, 1977)	Lakes (Wetzel, 1983)	Streams (Dodd et al., 1998)
Oligotrophic	<3	<3	<10
Mesotrophic	3-7	2-15	10-30
Eutrophic	7-55	10-500	>30
Hypereutrophic	>55	>500	

In the North Bosque River TMDL process, in-stream and laboratory bioassays were used to define the limiting nutrient within the system focusing on N and P. These bioassays along with in-stream water quality monitoring data were then used to develop predictive relationships for target development. Potential nutrient targets are proposed for limiting algae production as indicated by CHLA concentrations within the stream system.

Defining the Limiting Nutrient

Bioassays were run for the North Bosque River using two general methods to evaluate the limiting nutrient (N or P) to algal growth. The first used standard algal bioassay procedures as outlined by USEPA (1978) and APHA (1995) employing *Selenastrum capricornutum* Printz. In addition, a slight modification of this procedure was employed using native phytoplankton inoculum from Lake Waco. The standard algal bioassay procedure represented monthly trials over a two-year period for one site along the North Bosque River. This site was sampling site BO100 from the Texas Institute of Applied Environmental Research (TIAER) monitoring program and is located close to the mouth of the river near the city of Valley Mills. The standard algal bioassays were conducted at the Limnology Laboratory at Baylor University in Waco (Dávalos-Lind and Lind, 1999).

The second method used an in-stream periphytometer to measure *in-situ* nutrient limitations (Matlock et al., 1998). The in-stream periphytometer was deployed at five sites along the North Bosque River and at a reference site along Neils Creek, which feeds into the North Bosque River between the cities of Clifton and Valley Mills. Data collected represent three different time periods at each site as presented by Matlock and Rodriguez (1999).

Phosphorus was the element limiting growth of *S. capricornutum* and native phytoplankton for the North Bosque River as indicated from the standard algal bioassay evaluations (Table 2). The addition of nitrogen generally showed a very limited growth response, while the addition of phosphorus or nitrogen plus phosphorus produced very similar growth responses. The growth response of the native algae was generally less than that of the *S. capricornutum* indicating a potential adaptation of the *S. capricornutum* as a laboratory species to growth in a nutrient rich environment.

Table 2. Mean and standard deviation (n=25) of growth response to phosphorus and nitrogen additions (fluorescence of treatment minus control) for samples collected between December 1996 and November 1998 for North Bosque River site BO100 (Dávalos-Lind and Lind, 1999).

Treatment	*Selnastrum capricornutum*	Native Algae
P Addition	102 ± 85	36 ± 37
N Addition	3 ± 6	2 ± 6
N + P Addition	149 ± 84	46 ± 47

The periphytometer study in a similar fashion compared growth potential between a control treatment and nutrient added treatments (Table 3). In summary, all three trials at the reference site on Neils Creek indicated phosphorus as the limiting nutrient. The North Bosque River sites indicated phosphorus limitation more often than nitrogen limitation, although in this nutrient rich environment, the *in-situ* trials indicated that other factors, such as light limitation due to canopy cover, were more limiting to algal growth than either nitrogen or phosphorus.

Table 3. Summary of *in-situ* stream bioassay results (Matlock and Rodriguez, 1999).

Location	P-Limited	N-Limited	Co-Limited	Other	Total
North Bosque River Sites	4	1	2	7	14
	(29%)	(7%)	(14%)	(50%)	
Neils Creek (Reference Site)	3	0	0	0	3
	(100%)	----	----	----	

Evaluating Phosphorus as a Response Variable to Algal Growth

With phosphorus as the limiting nutrient, four general approaches were used to develop a predictive relationship between in-stream phosphorus and CHLA concentrations for target development. The first considered TNRCC screening levels for CHLA. The second used reference site values as a way of setting a benchmark for ecosystem expectations related to a minimally impacted watershed. The third evaluated the relationship of *in-situ* productivity compared to maximum potential productivity, as measured through the periphytometer bioassay study, in relation to in-stream phosphorus concentrations. The fourth method evaluated annual mean CHLA versus phosphorus concentrations from routine grab sampling data from sites throughout the Lake Waco watershed based on a saturating nutrient concept for CHLA production.

In evaluating a target, orthophosphate-phosphorus (PO_4-P) was chosen as the independent variable driving algal productivity and growth for four reasons. Unlike total-P, PO_4-P is not confounded with the dependent variable of algal biomass as measured by CHLA. Secondly, PO_4-P has been shown to predict algal population growth rates according to an external-substrate model (Monod 1950; Kilham 1978). This "Monod" model has been well supported by a number of laboratory and field studies of algal population growth (see Grover 1997 for a review). Third, aquatic ecosystems enriched through cultural eutrophication are known to have elevated and measurable levels of PO_4-P. This is in contrast to less productive natural systems where ambient PO_4-P concentrations are very hard to measure (e.g., Dillon and Rigler, 1974). Finally, PO_4-P is the largest component of bioavailable phosphorus in the North Bosque River as measured by the Sharpely (1993) method.

Monitoring data from January 1996 through December 1999 collected at eight stream sites along the North Bosque River was compared to TNRCC screening levels for CHLA, PO_4-P and total-P (Table 4). While 49% of CHLA samples exceeded the screening level of 16.1 μg/L, only 9% of phosphorus samples exceeded either the PO_4-P or total-P screening level. This does not indicate that phosphorus is not a problem in the North Bosque River or that phosphorus is not related to CHLA production, but these results are an artifact of the methodology used by the TNRCC in setting screening levels. These screening levels represent the 85 percentile of all stream data for the State of Texas and do not indicate a biological linkage between phosphorus and CHLA concentrations (TNRCC, 1999b). As the State of Texas has not adopted numeric criteria for nutrients and CHLA, the TNRCC has developed this methodology for determining classified waters that may be of concern due to nutrient or CHLA levels. For reference, USEPA is forming a strategy for developing regional numeric criteria for nutrients, but this guidance is not yet available (USEPA, 1998b). It is important to note that the TNRCC screening levels are not static and may change as the TNRCC annually re-evaluates water quality within the State's waters.

Table 4. Percent and (number) of North Bosque River samples exceeding TNRCC screening levels.

North Bosque River Samples Evaluated	Screening Level (TNRCC, 1999b) CHLA 16.1 µg/L	PO_4-P 0.91 mg/L	Total P 1.21 mg/L
430	49 % (211)	----	----
767	----	9% (70)	----
764	----	----	9% (65)

In comparing reference site values on Neils Creek to values along the North Bosque River, a much lower mean CHLA and PO_4-P was indicated for Neils Creek (Table 5). A much larger variation in values was noted for values along the North Bosque. This variation, in part, is accounted for by spatial variation in sampling sites and flow along the North Bosque River from upstream to downstream sites. In general, the highest concentrations of CHLA and PO_4-P are found in the upper reaches of the North Bosque River with decreasing concentrations from upstream to downstream locations (McFarland and Hauck, 1998; Pearson and McFarland, 1999). Using Neils Creek as a reference site, a mean CHLA of 4 µg/L could be expected at a PO_4-P concentration of 0.014 mg/L as a benchmark within this ecoregion.

Table 5. Basic statistics for monthly CHLA and bi-weekly PO_4-P samples from eight monitoring sites along the North Bosque River compared to reference site data on Neils Creek for January 1996 through December 1999.

	CHLA (µg/L)					
	Mean	Median	Std	Min	Max	# Obs.
North Bosque	27	16	34	0.5	290	430
Neils Creek	4	3	3	0.6	15	48
	PO_4-P (mg/L)					
	Mean	Median	Std	Min	Max	# Obs.
North Bosque	0.34	0.10	0.61	0.002	4.51	767
Neils Creek	0.014	0.009	0.014	0.002	0.08	86

The third approach involved use of the Lotic Ecosystem Trophic Status Index (LETSI). The LETSI is defined as the ratio of baseline primary productivity (BPP) to maximum potential productivity (MPP) where BPP is represented by the control treatment containing no added nutrients and MPP is represented by the N plus P treatment from the periphytometer bioassay method (Matlock et. al., 1999). The LETSI should vary between zero and one with a value of one indicating that the stream is at MPP. LETSI values from the bioassay treatments were compared to in-stream PO_4-P concentrations at the time of the periphytometer trials (Figure 2). In Figure 2, sites BO020, BO040, BO070, BO090 and BO100 represent locations along the North Bosque River. BO020 is located just above Stephenville and BO040 is located below Stephenville about a quarter mile below the discharge for the Stephenville wastewater treatment plant. Site BO070 is located just north of Hico, while sites BO090 and BO100 are located near the cities of Clifton and Valley Mills, respectively. Also included in Figure 2 are sites HC060 on Hog Creek, MB060 on the Middle Bosque River and NC060 on Neils Creek. In relation to algal productivity, sites BO020 and BO040 were at nutrient saturated production or MPP. It appeared that saturation of baseline production occurred at a PO_4-P concentration of about 0.2 mg/L. Site HC060 also indicated nutrient saturation, but factors other than phosphorus were considered to limit production at site. NC060, our reference site, had a LETSI of 0.4 at a PO_4-P concentration of 0.015 mg/L. A Michaelis-Menten equation was fit to the data using the Lineweaver-Burk parameter estimation method to calculate the half saturation constant (Lehninger, 1975). The LETSI reaches 50% at a PO_4-P of 0.04 mg/L, which was considered a potential target value.

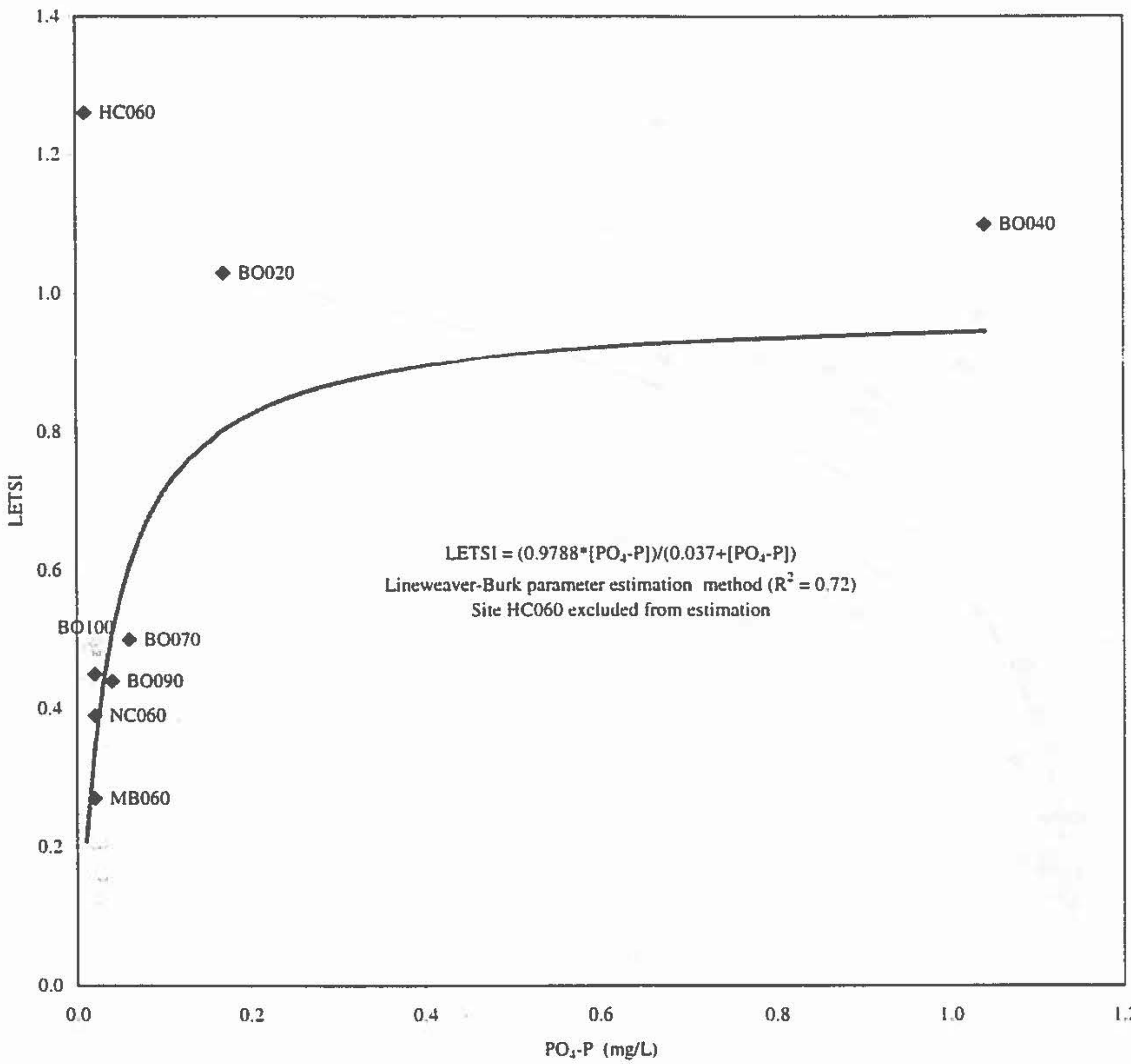

Figure 2. Average LETSI verses stream PO_4-P concentrations.

The fourth method used to relate CHLA to PO_4-P concentrations compared annual mean values of routine grab samples from sampling sites across the Bosque River watershed (Figure 3). A distinct break in the data was noted at a PO_4-P concentration of about 0.05 mg/L. Below 0.05 mg/L PO_4-P, CHLA concentrations were generally below 20 µg/L. Above 0.05 mg/L PO_4-P, mean annual CHLA concentrations appeared to plateau between 20 and 45 µg/L. In Figure 3, data from sampling site BO040 were excluded for clarity of presentation. At site BO040 on the North Bosque River, annual PO_4-P values ranged from 0.9 to 1.9 mg/L with annual CHLA concentrations generally greater than 20 µg/L.

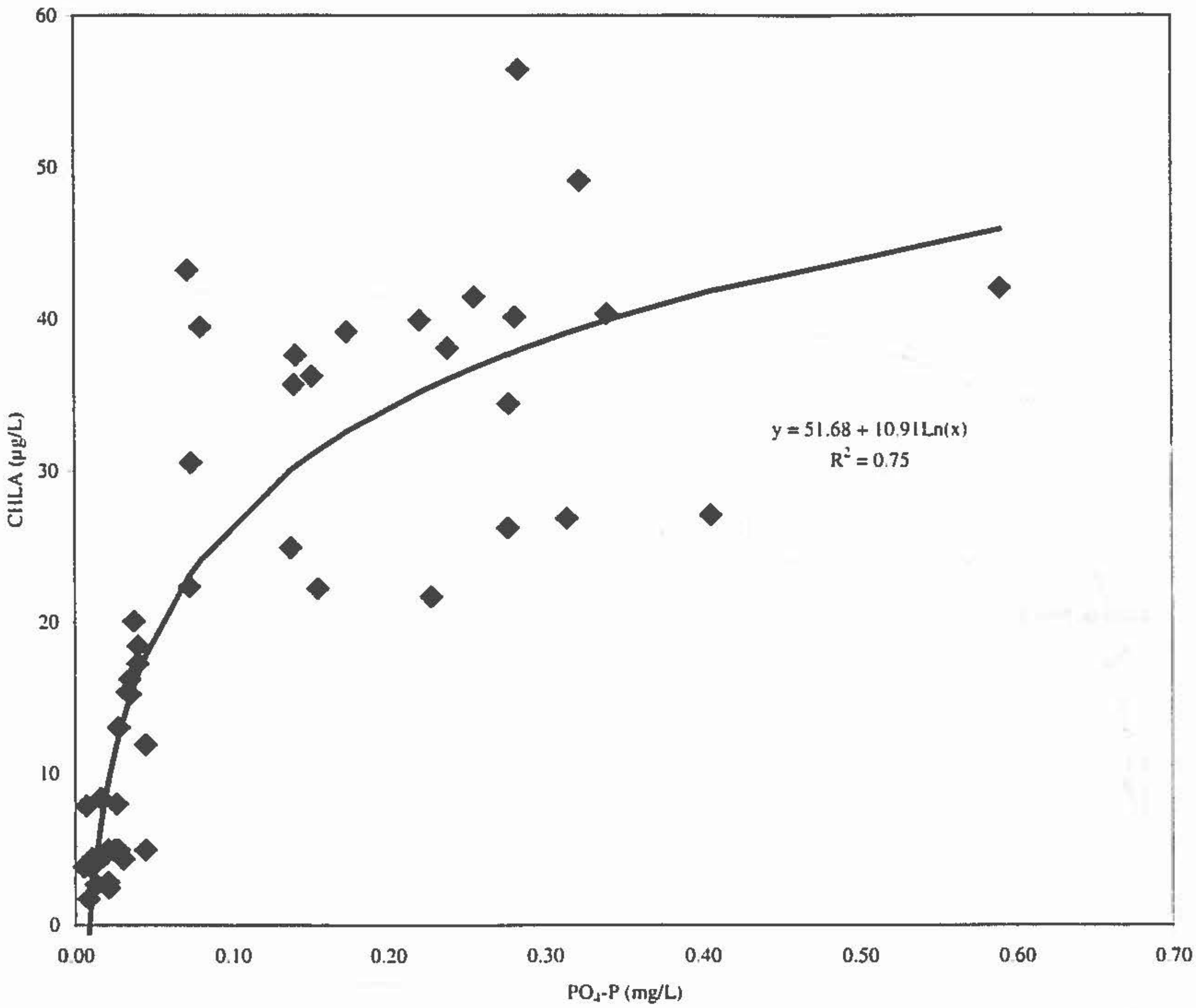

Figure 3. Comparison of annual average CHLA with PO_4-P concentrations.

A natural log function was fit to best describe the relationship between annual CHLA and PO_4-P concentrations. A PO_4-P concentration of 0.05 mg/L corresponded to a CHLA level of about 20 µg/L. For reference, a PO_4-P concentration of 0.038 mg/L corresponded to a CHLA level of 16.1 µg/L, the TNRCC screening level.

Summary of Potential Targets

From these relationships, a summary of potential PO_4-P targets was developed (Table 6) for presentation to the TMDL advisory committee and technical workgroup. These potential targets represent a preliminary analysis of the monitoring data for target development and should not be taken as a definitive analysis of the TMDL target for the North Bosque River. An initial target of 0.03 mg/L PO_4-P as an annual average for the North Bosque River at Meridian, Clifton and Valley Mills has been set. This target is being reviewed and a watershed-loading model (SWAT) is being applied to evaluate implications of management practices on the feasibility of meeting this proposed target.

Table 6. Summary of potential PO_4-P targets for controlling algal growth.

	PO_4-P	CHLA
Reference Site (NC060) –		
Mean Jan96-Dec99	0.014 mg/L	4 µg/L
Annual Mean	0.015 mg/L	4 µg/L
LETSI Productivity 50%	0.040 mg/L	Not Applicable
Annual Stream Data –		
Threshold Break	0.050 mg/L	19 µg/L
Mean at TNRCC CHLA	0.038 mg/L	16.1 µg/L
Range	0.014 – 0.05 mg/L	4-20 µg/L

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Managing Uncertainty from a Modeling Perspective

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Total Maximum Daily Load (TMDL)

- TMDL = WLA + LA + MOS
  WLA = Waste Load Allocation (point sources)
  LA = Load Allocation (nonpoint sources)
  MOS = Margin of Safety (uncertainty)

- MOS - required component
  - accounts for uncertainty in pollutant loads and receiving body water quality.......

Standard TMDL approach

- Define assessment endpoints
- Determine pollutant of concern
- Estimate assimilative capacity
- Quantify pollutant loading from all sources
- Determine allowable pollutant load
- Allocate loads among sources
- Develop management scenarios

TMDLs usually....

- use watershed as management unit
- involve monitoring
  (chemical - physical – biological)
- involve computer modeling
- provide information for management decisions

Why model?

- Understand complex watershed-level processes
- Fill gaps in monitoring data
- Identify sources of pollution
- Predict system response to change
- Evaluate management alternatives

Models

- "All models are wrong, some models are useful." George Box
- All models are a simplification of the real world.
- Models are heuristic tools - they teach us how complex systems may behave under specific conditions.

What is uncertainty?

- The condition of being in doubt.
- In TMDLs and watershed-level analysis, the only thing we are sure of is that we are in doubt!
- Uncertainty is a measure of risk.

Uncertainties

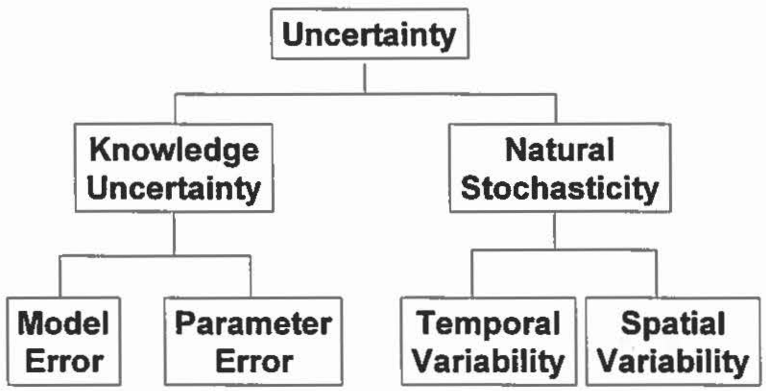
- Ubiquitous in TMDLs and watershed- level analysis
- Generally ignored
- Essential to quantify
- Quantification provides valuable information for decision making

Sources of Uncertainty

(as per Suter, 1993)

- Inherent randomness of the world (stochasticity)
- Imperfect or incomplete knowledge of things that could be known (ignorance)
- Mistakes in execution of assessment activities (error)

Uncertainty Taxonomy



Knowledge vs Stochasticity

- Knowledge error can be reduced through further measurement or improved models
- Stochasticity is a property of the natural system, usually not reducible

Propagation of Uncertainty

- Monte Carlo Simulation
  - Easy to use
  - Computer does the work
  - Not affected by nonlinearities or discontinuities
  - Robust
- First-Order Variance Propagation
  - Mathematically complicated
  - Difficult for complex models
  - Limitations (assumes linearity, magnitude of parameter CV < 10-20%)

Monte Carlo Simulation

1. Define statistical distributions of input parameters
2. Randomly sample from these distributions
3. Perform repeated model simulations using randomly selected sets of parameters
4. Analyze output statistically

Distributional Assignments

- Based on experimental data when possible
- Subjective distribution is okay
- Uniform (min, max)
  - Use when no site-specific data
- Triangular (mode, min, max)
  - Use when some site-specific
- Normal, Lognormal
  - Use when have experimental data
- NEVER hold uncertain parameter constant due to lack of data/distribution

Illustrative Example:

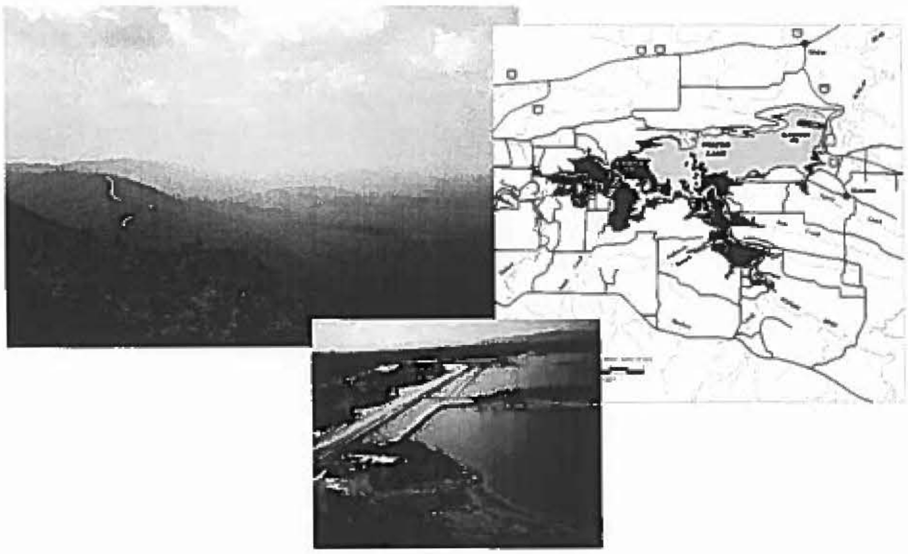
- Wister Lake in Oklahoma
- Monitoring (in streams and lake)
- Watershed-level modeling (EUTROMOD)
- Uncertainty analysis
- Management implications - given uncertainty

Wister Lake TMDL

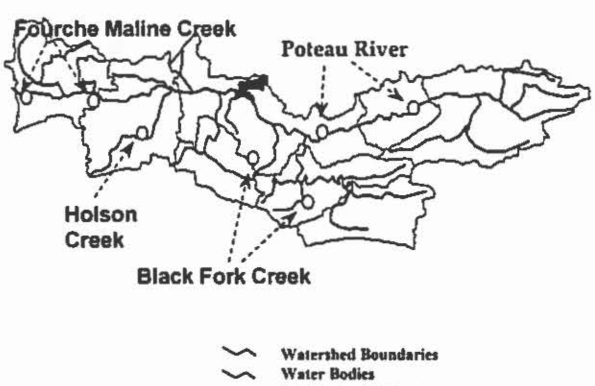
- Endpoint = lake trophic state
- Pollutant of interest = phosphorus
- EUTROMOD used to:
  - estimate assimilative capacity of lake
  - quantify pollutant loading from all sources
  - determine allowable pollutant loads
  - allocate pollutant loads

Study Area

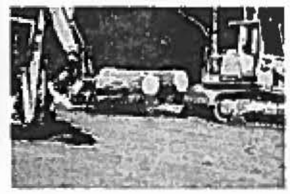
Wister Lake, Oklahoma



Monitoring Stations



Sources of Pollution



Geographic Information System

- Characterize watershed
- Locate pollutant sources
- Provide model input
- Produce pretty pictures

EUTROMOD Model

- Nutrient loading & lake response
- Annual loading estimates
- Predicts lake-wide, average annual conditions
- Spread-sheet based
- Developed by: Ken Reckhow, Duke

Model Modifications

- Converted to MS Excel
- Simulations by subwatershed
- Uncertainty analysis (@Risk)

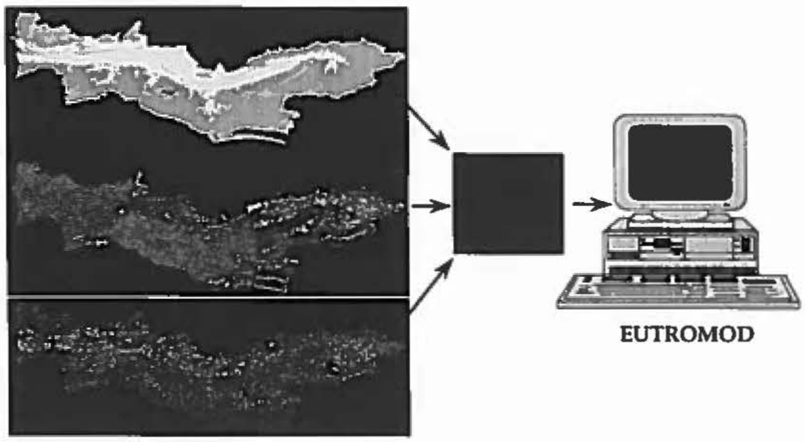
Model Details

- Rational equation (runoff)
- USLE (soil loss)
- Loading factors (nutrients: N & P)
- User-defined point source loading
- Regional regression equations (lake response: chlorophyll *a*, nutrients)

Model Inputs

- Climatic
  - precipitation, lake evaporation
- Watershed Characteristics
  - land use, soil factors
  - nutrient loading factors
  - delivery ratios
  - septic system and point source information
- Lake Morphology
  - surface area, mean depth

EUTROMOD Input from GIS



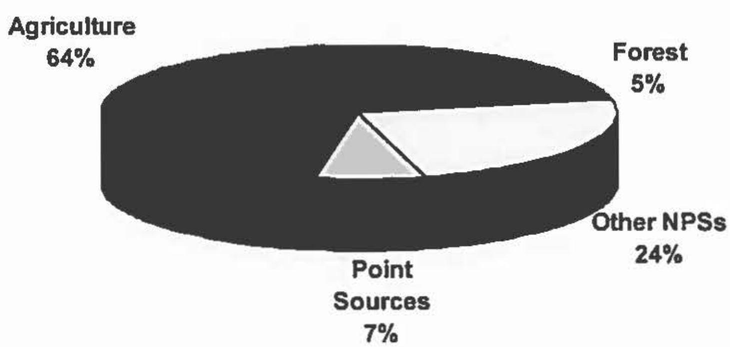
Model Outputs (annual averages)

- Runoff
- Erosion & sediment delivery
- Nutrient loads
- In-lake response
  - Nutrient concentrations (N, P)
  - Chlorophyll *a* concentration
  - Trophic state (Carlson's)

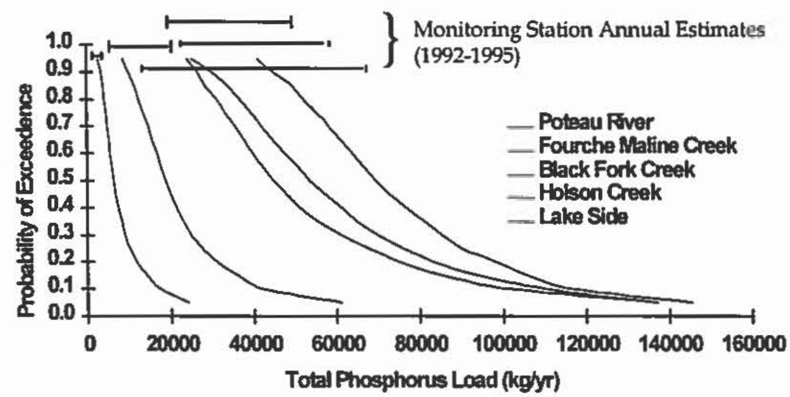
Uncertainty Analysis

- Monte Carlo simulations
- Stochasticity
  - temporal variability of rainfall (year-to-year)
- Model error
  - lumping error (USLE K- and LS-factors)
- Parameter error
  - 17 parameters from sensitivity analysis

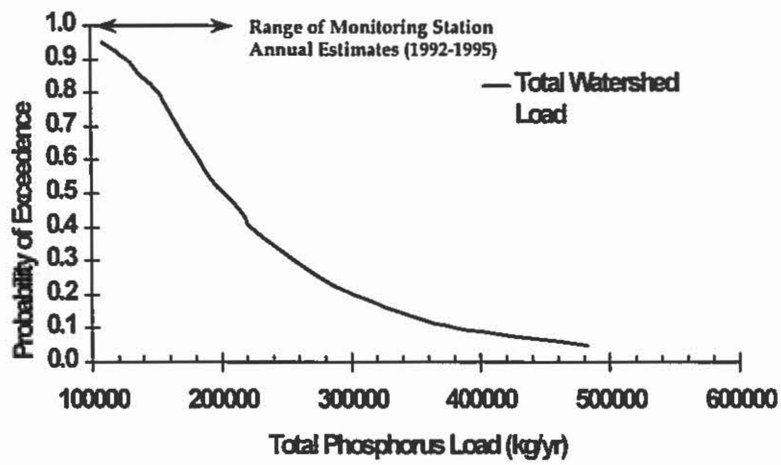
Total Phosphorus Loads by Source

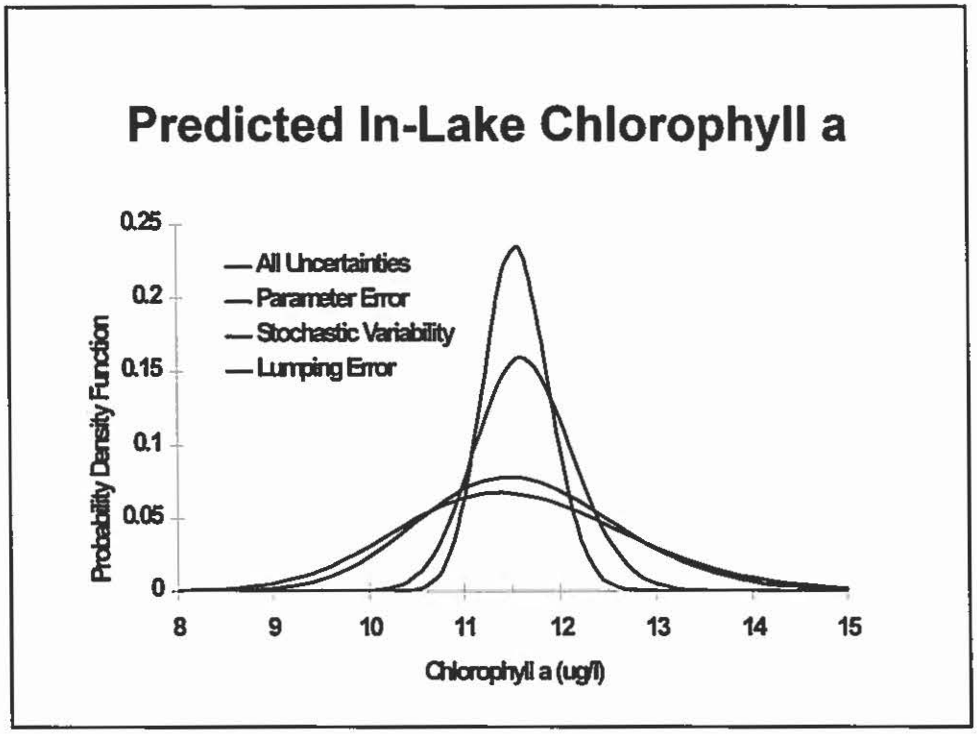


Predicted Phosphorus Loads by Subwatershed

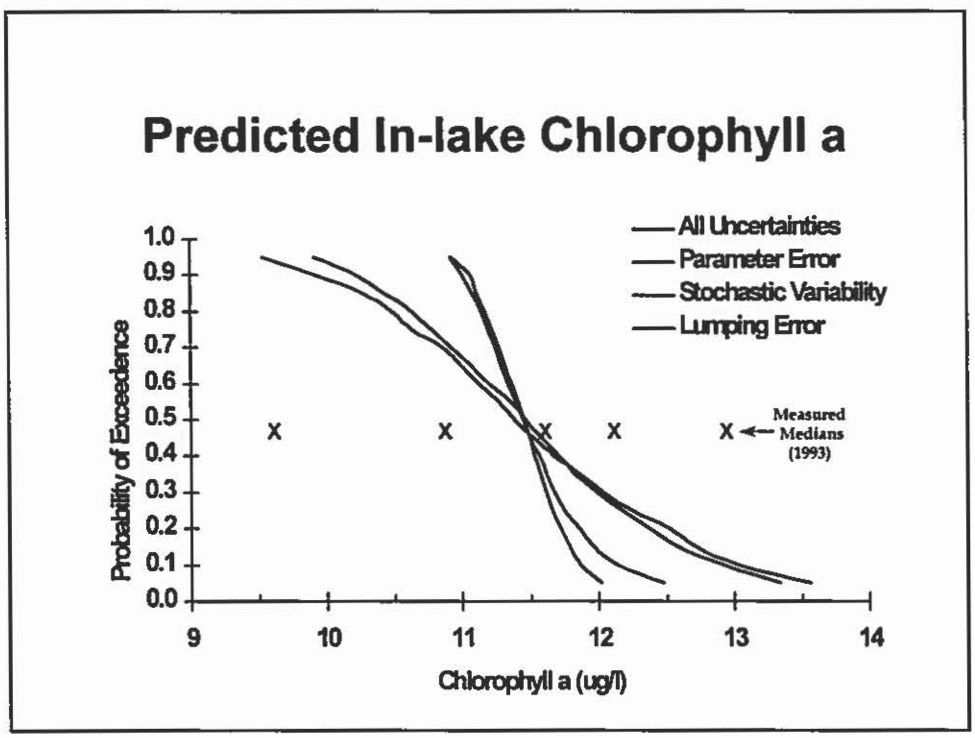


Predicted Total Phosphorus Loads



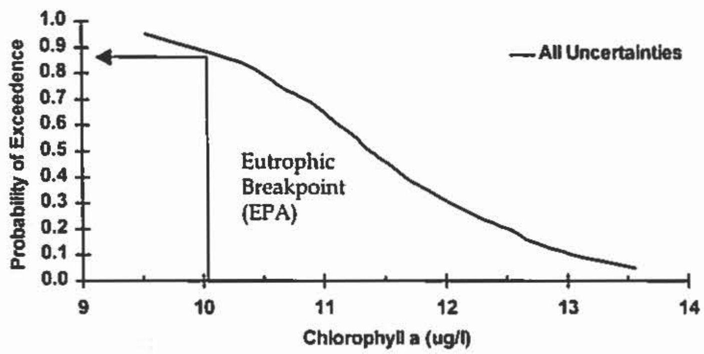


Predicted In-Lake Chlorophyll a
All Uncertainties
Parameter Error
Stochastic Variability
Lumping Error
Probability Density Function
0.25
0.2
0.15
0.1
0.05
0
8
9
10
11
12
13
14
15
Chlorophyll a (ug/l)

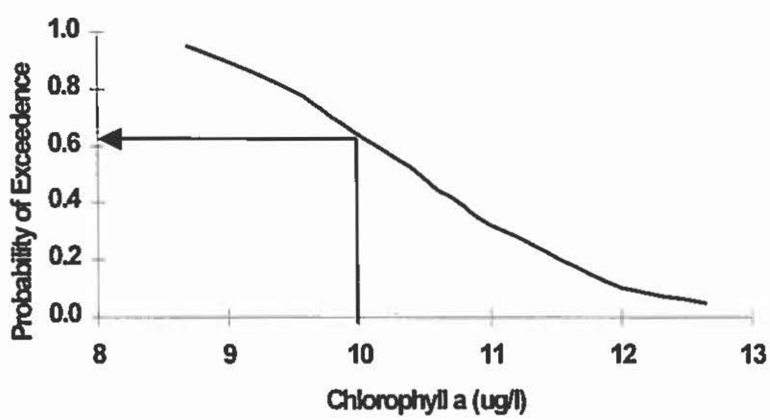


Predicted In-lake Chlorophyll a
All Uncertainties
Parameter Error
Stochastic Variability
Lumping Error
Probability of Exceedence
1.0
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0.0
X
Measured Medians (1993)
9
10
11
12
13
14
Chlorophyll a (ug/l)

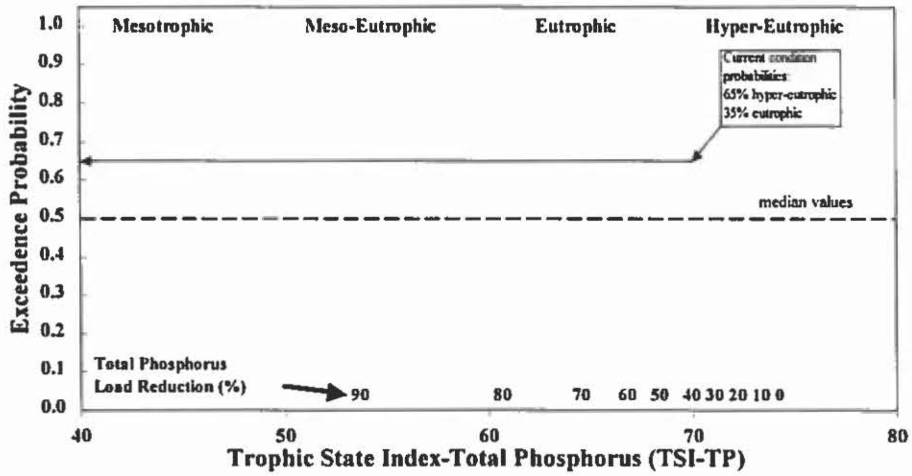
Probability of Trophic State



In-Lake Response to 40% Reduction in Agricultural Loads



Reduction Scenarios and Trophic State



Management Implications

- A single management decision results in a RANGE of environmental responses (varying spatially & temporally)
- Understanding the full range of possible outcomes provides valuable information
- Decisions can be based on probability of occurrence or level of RISK acceptable to resource managers
- Results can be used to target areas needing further study or more refined measurements

Summary

- Many uncertainties in watershed-level analyses
- Uncertainties are generally ignored
- Important to quantify uncertainties
- New tools make it easier to incorporate uncertainty analysis
- Uncertainty analysis can provide information for more knowledgeable decision-making
- Many additional uncertainties need to be quantified

University of Vermont

Civil and Environmental Engineering Department

Publications

- Hession and Storm. 2000. Watershed-Level Uncertainties… JEQ v29
- Hession et al. 1996. Risk analysis of TMDLs in an uncertain environment… JLRM v12
- Hession et al. 1996. A watershed-level ecological risk assessment… JAWRA v32

SECTION 3

Case Study: The Bosque River Watershed

TNRCC

Adopted February 2001

Two Total Maximum Daily Loads for Phosphorus in the North Bosque River

For Segments 1226 and 1255

Prepared by:
The Strategic Assessment Division, TNRCC

printed on recycled paper

TEXAS NATURAL RESOURCE CONSERVATION COMMISSION

Two Total Maximum Daily Loads for Phosphorus in the North Bosque River

Introduction

Section 303(d) of the Clean Water Act requires all states to identify waters that do not meet, or are not expected to meet, applicable water quality standards. For each listed water body that does not meet a standard, states must develop a total maximum daily load (TMDL) for each pollutant that has been identified as contributing to the impairment of water quality in that water body. The Texas Natural Resource Conservation Commission (TNRCC) is responsible for ensuring that TMDLs are developed for impaired surface waters in Texas.

In simple terms, a TMDL is a quantitative plan that determines the amount of a particular pollutant that a water body can receive and still meet its applicable water quality standards. In other words, TMDLs are the best possible estimates of the assimilative capacity of the water body for a pollutant under consideration. A TMDL is commonly expressed as a load, with units of mass per time period, but may be expressed in other ways also. TMDLs must also estimate how much the pollutant load needs to be reduced from current levels in order to achieve water quality standards.

The Total Maximum Daily Load Program, a major component of Texas' statewide watershed management approach, addresses impaired or threatened streams, reservoirs, lakes, bays, and estuaries (water bodies) in or bordering the state of Texas. The primary objective of the TMDL Program is to restore and maintain the beneficial uses (such as drinking water, recreation, support of aquatic life, or fishing) of impaired or threatened water bodies.

These TMDLs are meant to achieve significant reductions in the annual-average concentration and total-annual loading of soluble phosphorus in the North Bosque River.

Section 303(d) of the Clean Water Act and the U.S. Environmental Protection Agency's (EPA) implementing regulations (40 Code of Federal Regulations, Part 130) describe the statutory and regulatory requirements for acceptable TMDLs. The TNRCC guidance document, *Developing Total Maximum Daily Load Projects in Texas* (GI-250), further refines the process for Texas. Following these guidelines, this TMDL document describes six elements which are summarized in the following sections:

- Problem Definition
- Endpoint Identification
- Source Analysis
- Linkage Between Sources and Receiving Waters
- Margin of Safety
- Pollutant Load Allocation

These TMDLs were prepared by:

- the TMDL Team in the Strategic Assessment Division of the Office of Environmental Policy, Analysis, and Assessment of the Texas Natural Resource Conservation Commission.

Significant assistance was provided by:

- the Texas Institute for Applied Environmental Research (TIAER) at Tarleton State University in Stephenville, Texas
- the Bosque River Advisory Committee (BRAC)
- the Texas State Soil and Water Conservation Board (TSSWCB)
- the Blackland Research and Extension Center (Blackland)

The two TMDLs described in this document were adopted by the Texas Natural Resource Conservation Commission on February 9, 2001. Upon adoption, the TMDLs became part of the Texas Water Quality Management Plan. The Texas Natural Resource Conservation Commission will use this document and the Texas Water Quality Management Plan in reviewing and making determinations on applications for wastewater discharge permits and in its nonpoint source pollution abatement programs.

Background Information

The North Bosque River (Segments 1226 and 1255) was included in the 1998 Texas CWA § 303(d) List and deemed impaired under narrative water quality standards related to nutrients and aquatic plant growth. Recent studies have indicated that under most conditions phosphorus is the limiting nutrient in the North Bosque River basin (Kiesling et. al., draft), and that dairy waste application fields and municipal wastewater treatment plants are the major controllable sources of phosphorus (McFarland and Hauck 1995, 1997, 1998, 1999a, 1999b). Watershed modeling for the North Bosque River TMDL assessed source categories of urban stormwater runoff, municipal wastewater treatment plants, wood/range land, pasture, row crops, non-row crops, and dairy waste application fields (Santhi et al 2000a, 2000b). The wood/range land use approximates the natural background condition of the watershed prior to development.

Evaluation of water quality conditions in the North Bosque River cannot be expressed exclusively in quantitative terms because the bases for including these segments on the impaired water body list are not related to violations of specific numeric criteria, but rather to narrative standards concerning nutrients and excessive algal growth. The Texas Surface Water Quality Standards [30 TAC, Chapter 307.4 (e)] say:

> "Nutrients from permitted discharges or other controllable sources shall not cause excessive growth of aquatic vegetation which impairs an existing, attainable, or designated use. Site-specific nutrient criteria, nutrient permit limitations, and/or separate rules to control nutrients in individual watersheds will be established where appropriate after notice and opportunity for public participation and proper hearing."

While there is little debate that nutrients in excessive amounts can create a situation conducive to the proliferation of algae and other aquatic plants, the quantification of what constitutes excessive algal and aquatic plant growth and the most effective means to control that growth is more elusive. Determination that a narrative standard has been violated is inherently a subjective exercise, so determination of desired endpoints and allowable loading is also largely subjective. Objective science may establish linkages between nutrient loading and water body trophic status, but subjective human values then determine or influence selection of the desired trophic level for a particular water body. Natural waters exhibit a range of trophic levels, that may vary geographically at any moment or may vary through time at any location. Natural sources often provide sufficient nutrients to support algal communities or blooms when other environmental conditions are favorable. The algae and aquatic plant growth supported by nutrients constitute the basal level of the aquatic food chain, so entirely depleting a water body or system of nutrients would undermine its ecology. Selection of appropriate nutrient endpoints must balance consideration of what is ecologically and technologically feasible against the subjective conditions favored by humans at any particular site.

When nutrients are the primary limiting factor for aquatic plants in a flowing stream, the most controllable nutrient is usually phosphorus. In the case of the North Bosque River segments, instream algal growth potential evaluations provided strong evidence that phosphorus is a controlling factor in the growth of aquatic plants (Matlock et. al. 1999a, 1999b). Evaluation of in-stream water quality data provided an estimate of the annual-average soluble phosphorus concentrations that are likely to limit the growth of aquatic plants in portions of the river (Kiesling et. al., draft). However, it must be noted that a number of other factors such as temperature, stream flow, light availability, and seasonal variations influence and may control the growth of aquatic plants in a river system. The ecologic interplay of the numerous limiting factors, combined with the subjective nature of nutrient standards or goals, makes determination of precise nutrient limits very difficult.

Local stakeholder participation in TMDL development was coordinated through the Bosque River Advisory Committee (BRAC), which was initially formed in 1996 to address some of the social and political issues associated with delineation and mitigation of regional water quality issues. The committee membership included elected officials (state senator and representatives, county judges and commissioners, city mayors), watershed residents representing dairies (large and small), row crop farmers, non-agricultural industry, and citizens with general interest in water quality. Representatives of several agencies involved in local TMDL or Concentrated Animal Feeding Operation (CAFO) issues served as resources to support the stakeholder process. Advisors and staff for the committee members also participated. The stakeholder committee was also supported by a Technical Work Group consisting of professionals from universities, institutes, and state and federal agencies. The Technical Work Group provided peer review of and consultation for the technical analyses performed for the TMDL.

The endpoint for this TMDL is a significant reduction in soluble reactive phosphorus (SRP) average total-annual loading and annual-average concentrations, as measured in the river at various sites. The goal is expressed as a "percent reduction" relative to the initial (i.e. current or existing) condition at the respective sites. The numeric statement of the goal of these North Bosque River TMDLs is to reduce average total-annual loading of SRP by approximately 50% for the entire North Bosque River watershed. That is predicted to reduce annual-average SRP concentrations in the river by approximately 47%, as a long-term watershed average and with some local variation that reflects location within the watershed and along the river.

Problem Definition

The Bosque River is located in north central Texas, northwest of the City of Waco, and is a tributary of the Brazos River. The Bosque River is impounded at Waco, near its confluence with the Brazos River, to form Waco Lake (Segment 1225), which provides water for approximately 150,000 people. The North Bosque River is the longest arm of the Bosque system, draining approximately 75% of the Waco Lake watershed, while the Middle and South Bosque Rivers and Hog Creek drain most of the remaining area (Figure 1).

Topographically and historically, the Bosque River watershed is representative of the heart of Texas. The upper watershed has medium-sized hills, carved into a limestone plateau, with relatively shallow, rocky soils and areas of moderate to steep slope. The upper watershed has long been utilized for ranching, dairies, and other animal production agriculture. The lower watershed, drained by the Middle and South Bosque Rivers, has rolling blackland prairie with deep soils, and row crop production is the predominant form of agriculture. The distribution of these and other land uses within the watershed is depicted on Figure 2.

The North Bosque River is administratively divided between two designated water quality segments (see Figure 1):

- <u>Segment 1226, North Bosque River</u> – extends from a point 100 meters up-stream of FM Road 185 in McLennan County to a point immediately upstream of the confluence of Indian Creek in Erath County
- <u>Segment 1255, Upper North Bosque River</u> – extends from a point immediately upstream of the confluence of Indian Creek in Erath County to the confluence of the North Fork and South Fork of the North Bosque River in Erath County

Designated uses for both segments of the North Bosque River are established in the Texas Surface Water Quality Standards (30 TAC Chapter 307). The 1998 Texas 303(d) List identified the North Bosque River segments as "impaired" by high levels of nutrients, based on exceedance of screening criteria used to assess support of narrative standards. These total maximum daily load (TMDL) allocations were developed to address nutrient loading and algal growth, and to support plans for attaining and maintaining water quality standards in the North Bosque River. Actions that reduce nutrient loading in the North Bosque River watershed will also improve or protect water quality in downstream water bodies.

Recent studies have indicated that phosphorus is the limiting nutrient in the watershed under most conditions (Matlock et. al. 1999a, 1999b). Studies also indicated that soluble phosphorus, which was analytically measured as soluble reactive phosphorus (or ortho-phosphate phosphorus), was a major form of phosphorus in the North Bosque River and statiscally better correlated to algal levels than total phosphorus (Kiesling et. al., draft). These TMDLs focus on controlling soluble phosphorus loading and stream concentrations to attain and protect designated uses.

Endpoint Identification

The water quality standard that was the basis for including the North Bosque River segments on the 303(d) List is narrative in nature. There are currently no established numeric criteria for nutrients in Texas.

Studies in the North Bosque River watershed to support development of these TMDLs included biological experiments and chemical analyses to estimate critical nutrient species and concentrations for the local streams. Instream periphytometers were used to assess algal productivity (measured as periphytic chlorophyll-α production) relative to nitrogen and phosphorus concentrations, which led to the determination that phosphorus is the limiting nutrient under most conditions (Matlock et. al. 1999). Analyses of stream nutrient and chlorophyll-α data then supported estimation of an annual-average soluble phosphorus concentration likely to exert some limitation on algal growth potential (Kiesling et. al., draft). Scientific techniques and statistical approaches used to develop preliminary phosphorus targets were discussed extensively by the Technical Work Group. The conclusion was that annual-average soluble reactive phosphorus (SRP) concentrations of 50 micrograms per liter (µg/L) or less would have a limiting effect on stream algal communities. As a lower bound for a target range of annual-average phosphorus concentrations, data from the least-disturbed reference stream in the watershed (Neils Creek) were assessed. That assessment indicated that an annual-average SRP concentration of 15 µg/L approximates least-disturbed natural conditions. Thus, biological and chemical data established that achieving annual-average phosphorus concentrations between 15 and 50 µg/L would probably have a significant limiting effect on algal growth. A "preliminary target" concentration within that range, i.e. 30 µg/L, was estimated for a monitoring station immediately upstream of Meridian, and related to a monitored mid-1990s average concentration at the same site of 60 µg/L. As a gross estimate, a 50% reduction in loading was presumed needed to attain a 50% reduction in average concentration in the vicinity of Meridian.

Parts of the upper reaches of the North Bosque River (i.e. Segment 1255 and the upper part of Segment 1226, or generally upstream from Iredell), and many tributary streams in that area, are intermittent in natural flow. In a section of the Upper North Bosque (Segment 1255), some dry weather flow is maintained primarily by wastewater treatment plant (WWTP) discharge from the City of Stephenville – but the length of that section varies due to the effect of weather conditions. As a result, there is effectively a technological lower limit on feasibly attainable nutrient concentrations within the zone affected by the Stephenville discharge. The upper-reach nutrient concentrations vary widely over time because storm runoff provides most flow other than the WWTP discharge, with relatively little baseflow from groundwater to buffer or limit the variability. Intermittent sections of stream channels, whether in tributaries or in the main stem river, typically contain terrestrial or wetland plant growth that can provide natural nutrient loading sufficient to support algal growth during wet periods. Consequently, algal growth in the upper reaches is probably more likely to be limited by light and/or water availability than by nutrient availability or temperature (i.e. when water and light are available, algae can grow; temperature and nutrients would seldom be limiting factors). For these reasons, nutrient concentration targets to assure control of aquatic plants are even more difficult to establish for intermittent stream reaches, and less certain to be ecologically meaningful.

The North Bosque River TMDLs are meant to achieve significant reductions in the total-annual loading and annual-average concentration of soluble phosphorus in the North Bosque River. Compared to existing conditions, the TMDLs are recommending average total-annual load reductions ranging from about 39% to about 62%, depending on the site monitored, with an average overall reduction of approximately 50% in soluble phosphorus average total-annual loading. Those load reductions are expected to reduce the average annual-average concentrations of soluble phosphorus by about 33% to 60%, depending on the site monitored. Because of the inherent natural variability of nutrient loading, "average" conditions or targets will be exceeded on occasion. Post-TMDL monitoring of soluble phosphorus concentrations in the North Bosque River will utilize probability curves developed from model analyses to determine if the long-term response of the system meets expectations.

Soluble phosphorus reductions of that magnitude (i.e. around 40% to 60%, loading or concentration) will reduce the potential for problematic algae growth in the North Bosque River and downstream waters, and should reduce the actual occurrence of algal blooms. Model simulations predict that the annual-average soluble phosphorus concentration in the North Bosque River at Valley Mills will be low enough to limit algal growth during 90 to 95% of the years following implementation (see Figure 4). Algal growth potential will also be significantly reduced at the upstream stations, although to a lesser degree than at Valley Mills (Figures 5 through 8). However, algae and nutrient interactions are extremely dynamic, and very much influenced by weather conditions and other environmental factors. Human efforts to control nutrient loading can reduce or limit the occurrence of algal blooms, but cannot totally prevent them in living water bodies. The model analyses predict, as shown in Figures 4-8, that these TMDLs will improve water quality conditions (i.e. reduce nutrient loads and concentrations) every year, but that some years will still exceed the most desirable range of annual-average soluble phosphorus concentrations.

Source Analysis

During the 1980s, the dairy industry expanded very rapidly in the North Bosque River and adjacent watersheds, to the extent that Erath County became the leading county for milk production in the state. The total number of milk cows in the watershed grew tremendously, with the current total in the neighborhood of 41,000 head. In keeping with current trends in the dairy industry, operations in this watershed also shifted from relatively small dairies dispersed over the landscape, to large dairies that tend to cluster together for economic and cooperative reasons. At the time data were collected to support this evaluation, 104 of the 105 dairies operating in the Bosque River Basin were located in the watershed of Segments 1226 and 1255 of the North Bosque River. The majority of those 104 dairies are in the upper half of the North Bosque River watershed, with the primary concentration within Erath County. Portions of Erath County that are not in the Bosque River watershed (see Figure 1) also contain numerous dairy operations, such that Erath County alone contains more dairy cattle than the entire Bosque River watershed.

Extensive data collection and scientific studies were performed during the 1990s, primarily in the Upper North Bosque River watershed, to assess the water quality effects of dairy practices. Those studies characterized nutrient loading from sources categorized as urban stormwater runoff, municipal wastewater discharges, wood/range land, pasture, non-row crops, row crops, and dairy waste application fields (McFarland and Hauck 1998, 1999a, 1999b). The percentage of gross annual loading provided by each of these sources depends on the location at which loading is summarized, since land uses and wastewater discharge are not evenly distributed across all subwatersheds (see Figures 2 and 3; McFarland and Hauck 1999a). Citizen stakeholders and technical experts involved in development of the North Bosque River TMDL agreed that the data indicate the major controllable sources of nutrients in the North Bosque River basin to be municipal wastewater treatment plants (WWTPs) and dairy waste application fields (WAFs). Of the other sources, only urban stormwater is controllable via an existing regulatory program. Loading contributed by urban stormwater is relatively small compared to other storm-event-driven loading within the watershed. However, if needed later to achieve the goals of these TMDLs, urban stormwater management to reduce phosphorus loading could be required by stormwater permits.

WWTPs are classic *point sources*, long regulated by state and federal permitting programs. WWTP discharges have been analyzed (modeled) as distinct point sources, and will be controlled as needed via the existing permit programs. Urban stormwater is also legally defined as a point source subject to permit requirements, but the hydrologic occurrence of urban runoff and geographic distribution of discharge points are more similar to nonpoint sources from a modeling perspective. The areas in which cattle are fed or confined at dairy operations are subject to Concentrated Animal Feeding Operation (CAFO) permits because they are legally considered point sources. Runoff from areas such as lots, feed lanes, and milking areas is regulated as point source, but runoff from dairy WAFs is not covered by CAFO permits and is treated as a nonpoint source. There are also dairies that are small enough to not require CAFO permits, but are considered to be small Animal Feeding Operations (AFO) and required to operate in compliance with Texas State Soil and Water Conservation Board (TSSWCB) guidance or TNRCC rules. Small AFOs are considered to be nonpoint sources, and regulated as such. Measures to control nutrient loading from WAFs may include a combination of CAFO permit conditions regulating land application of CAFO wastes, watershed rules that affect all AFO operations, and voluntary programs.

The source categories of urban stormwater, wood/range land, pasture, non-row crops, row crops, and dairy waste application fields (WAFs) were analyzed (modeled) as *nonpoint sources*. Of these, only the urban stormwater and WAFs are associated with activities that may require permits. Among these nonpoint categories, the largest sources of phosphorus loading in the North Bosque River basin are wood/range land and WAFs (Figure 3). The wood/range land use is considered to be the *background* condition of the watershed, because those areas are relatively natural in character and contribute a large percentile to the loading summary only because that land use occupies a large amount of the watershed area. On the other hand, the WAFs occupy a relatively small area of the watershed, but contribute a disproportionately large share of the nutrient loading.

Figure 2 illustrates the distribution of land use within the Bosque River watershed. Municipalities with permitted WWTP discharges are listed in Table 1.

Table 1. Municipal WWTP Flows (daily average in Million Gallons per Day – MGD)

City	Permitted Flow	Recent Flow	Estimated Yr 2020 Flow **
Clifton (old)	0.400	0.303	NA
Clifton (new)	0.650	NA	0.372
Hico	0.200	0.086	0.089
Iredell	0.050	0.024	0.033
Meridian	0.450	0.157	0.251
Stephenville	3.000	1.939	2.629
Valley Mills	0.360	0.101	0.103
Total *	4.710	2.610	3.477

(* Total permitted flow uses new Clifton facility) (** from Easterling 2000)

Population projections for 20 years in the future for each of the municipalities with permitted WWTPs were prepared for assessing future growth conditions (Table 2; Easterling 2000).

There are 104 dairies operating or authorized within the North Bosque River watershed. Of those, 66 are CAFOs operating under individual or general permits, while 38 are AFOs that are not required to obtain permits but must operate such that they do not cause water quality problems.

Table 2. Estimated Urban Population Growth within the North Bosque River Watershed		
City	Year 2000	Year 2020
Clifton	3,557	4,268
Hico	1,380	1,417
Iredell	433	581
Meridian	1,504	1,791
Stephenville	16,060	21,103
Valley Mills	1,090	1,118
Total	24,024	30,278

The existing gross annual loadings above (upstream of) each of the five North Bosque River index stations were estimated using water quality analyses and land use information (McFarland and Hauck 1999a). This served to establish approximate percentile contributions to the gross loading by each source or land use type. Those gross annual loads, and the percent contributions by source type, are shown in Figure 3. The percent contributions by source category are also shown in Table 3.

Table 3. Estimated Percent of Total Gross Annual Load by Source Type					
Source	Above Stephenville	Below Stephenville	Above Meridian	Clifton	Valley Mills
urban runoff	2 %	6 %	6 %	6 %	6 %
row crop	0 %	0 %	2 %	4 %	5 %
non-row crop	2 %	2 %	2 %	1 %	1 %
pasture	9 %	5 %	7 %	8 %	9 %
wood/range	7 %	5 %	18 %	22 %	24 %
WWTP	0 %	28 %	10 %	9 %	10 %
WAF	80 %	54 %	55 %	50 %	45 %
Column totals (%)	100 %	100 %	100 %	100 %	100 %

Linkage Between Sources and Receiving Water

Data collected during the 1990s were used to develop and calibrate a watershed model of the Bosque River basin. The model program used was the Soil and Water Assessment

Tool, or SWAT (Arnold et al 1998; Arnold et al 1999; USDA-ARS 1999), which is designed for assessing large-scale agricultural management and water quality issues, and is supported by the U.S. Department of Agriculture - Agriculture Research Service. Preparation of a Bosque River application of SWAT was a joint effort by the Texas Institute for Applied Environmental Research (TIAER) and the Blackland Research and Extension Center (Blackland), with TIAER providing some of the input data and Blackland staff operating the model (Santhi et al 2000). The Bosque River application of SWAT is the primary technical tool for linking watershed sources, land use, and management practices to receiving water responses.

The SWAT model is dynamic, or time-variable, using a one-day time step and capable of simulating periods ranging from a few weeks to many years. Model inputs define subwatersheds within which management measures (i.e. crops, timing of irrigation or fertilizer applications, etc.), soil types and topography, and weather conditions can be stipulated. For each day of simulation, the model uses the weather input, subwatershed characteristics and management practices, crop growth effects, and other physical processes approximated by the model algorithms, to calculate the amount of water and associated constituents leaving the subwatershed outlet. Constituents simulated may include sediment, particulate and soluble forms of nutrients, and pesticides. A flow routing component of the model transports flow and loading from each subwatershed across the subsequent subwatersheds while accumulating the subwatershed contributions. First-order decay kinetics were calibrated to allow the flow routing component of SWAT to also account for assimilation of soluble phosphorus (i.e. via conversion to biomass or adsorbtion to soil particles).

Initial steps towards the Bosque River application of SWAT involved definition and characterization of the modeled watershed. Land use, soils and topographic information were used to determine subwatersheds and their individual characteristics. Precipitation and temperature data were collected and formatted to drive model simulations of recent historical periods.

Water quality data were collected and analyzed to characterize the river response during a monitoring period in the mid-1990s. Then, the model was calibrated by simulating a period of time during which input factors (i.e. rainfall, land uses and management, etc.) and output factors (i.e. water quality, nutrient concentrations in stream) were known, and adjusting model kinetics or input parameters until the observed (i.e. real life) conditions were reproduced as closely as possible by the model output. Once calibrated, the model was ready for use in TMDL analyses (Santhi et. al. 2000a, 2000b).

In order that the model simulations should account for the variability in nutrient concentrations or loading that occur due to normal variations in weather, the SWAT runs simulated a 39-year period using actual records of daily rainfall and temperature for the years 1960 through 1998. For predictive purposes, those years are assumed to represent the usual range of weather conditions that are likely to occur – although future weather cannot be expected to occur in precisely the same sequence.

If plotted directly, the raw model output produces a time series of SRP concentrations that reflect temporal variability, which appears erratic and very difficult to interpret. So, review of model output focused on predicted annual-average SRP concentrations, which was justified because of both model calibration and TMDL implementation considerations. In calibration, model-predicted monthly-average and annual-average SRP concentrations compared well to observed concentrations, but predicted daily concentrations compared less well. Other nutrient TMDLs have used long-term averages as targets rather than daily concentrations. These considerations supported defining annual-average SRP concentration as an appropriate parameter for post-TMDL monitoring.

In order to enhance model output interpretation and target evaluation, the SWAT-predicted annual-average SRP concentrations for the 39 simulated years were developed into exceedance probability graphs by ranking the annual results from highest to lowest and plotting exceedance probabilities for each annual value. The SWAT simulations kept land uses and management measures constant while weather conditions were dynamically simulated for a representative 39-yr period, so the resulting variation in the model output represents the effect of hydrologic variability. The resulting figures (see Figs. 4 through 9) can thus be read as indicating the probability that a particular annual-average concentration (or total-annual load) will be equaled or exceeded during any random year, or as the frequency at which a particular annual-average concentration will be equaled or exceeded during any group of years. For instance, in Figure 4, looking at the line representing the "TMDL-e" case in the concentration-based graphs, above the 0.2 exceedance probability marker, one reads the figure as predicting that the annual-average concentration would be greater than or equal to (approximately) 29 parts per billion (ppb) in 20% of future years, and less than or equal to 29 ppb in 80% of future years. For the purposes of these TMDL analyses and discussions, parts per billion (ppb) and micrograms per liter (µg/L) are considered to be equivalent units, and are used interchangeably.

Numerous predictive model scenarios were simulated to provide insights concerning the linkage between watershed conditions, management practices, and instream water quality. Scenarios represented in this report include:

Existing –	represents conditions extant during the mid-1990s; uses actual flows and concentrations of WWTPs, actual dairy cow numbers (40,450) and WAF areas, etc., as measured during the monitoring/calibration period
Future –	represents "full permitted" conditions for WWTPs and dairies, and projected urban populations and areas 20 years in the future; uses maximum number of dairy cows (66,930) allowable under existing permits with corresponding WAF area, and maximum permitted WWTP flows with phosphorus concentrations as measured during monitoring period; includes hypothetical 0.6 million gallons per day (MGD) discharge to represent new point sources

TMDL-e – incorporates management measures for WAFs and WWTPs, using populations, WWTP flows, dairy cow numbers and WAF area corresponding to mid-1990s monitoring period; represents anticipated effect of TMDL under "existing conditions"

TMDL-f – incorporates management measures for WAFs and WWTPs, using populations, WWTP flows, dairy cow numbers and WAF area corresponding to 20 years growth and full permitted limits; represents anticipated effect of TMDL under "future growth" conditions; includes hypothetical 0.6 million gallons per day (MGD) discharge to represent new point sources

Nonpoint only – same as TMDL cases except that WWTPs remain at "existing" conditions; provides a way to estimate how much load or concentration reduction at the river index sites was due to nonpoint source management practices on WAFs only, which also provides estimates for the amount of reduction due to WWTP measures.

The "existing condition" model scenario provides the initial or reference values for calculating percent reductions, and the "TMDL-e" model scenario defines the amount of reduction possible if a hypothetical suite of management measures is imposed on existing conditions. Similarly, the "future growth" model scenario provides the reference values, and the "TMDL-f" scenario estimates the amount of reduction, for calculating percent reductions that would occur under full-permitted and 20-year growth conditions.

Discussion of percent reduction targets are based on long-term averages derived from the model results. Each model run produced 39 total-annual loads and 39 annual-average concentrations representing each year included in the simulation. Plotting those sets of 39 values produced the model output figures shown in Figures 4-9. The long-term averages used for target discussions were determined by calculating the arithmetic mean for each set of 39 values. The calculated long-term averages are depicted as horizontal lines crossing the "existing" and "TMDL-e" plots for concentration and load in Figures 4-8.

Results from the model runs, as illustrated in Figures 4 through 8, indicate that the management measures simulated can significantly reduce total-annual loading and annual-average concentration of SRP throughout the North Bosque River watershed, and thus in downstream water bodies as well. The model results also indicate that lower soluble phosphorus loads and concentrations will occur every year, although the natural variation caused by weather and other environmental conditions will cause some years to still exceed the most desirable levels. Stated another way, "better conditions" will occur every year at all locations, "desirable conditions" will occur more often and at more locations, and "undesirable conditions" will occur less often at fewer locations. In particular, annual-average concentrations in the lower river reaches (i.e. at Clifton and Valley Mills) are predicted to be less than the 50 μg/L biological limitation concentration derived from periphytometer studies and in-stream water quality data analyses, in most years.

Model results from "Above Stephenville" (Fig. 8) characterize a subwatershed that contains no permitted WWTP discharges, but does contain numerous dairy operations and WAFs. Annual load and concentration reductions predicted for that subwatershed area are considered to be representative of how the simulated management measures would affect phosphorus loading and water quality in other dairy-dominated subwatersheds. This result demonstrates that the simulated suite of management measures would also cause significant improvement to water quality conditions in unclassified tributary streams that have no point source discharges and contain dairy operations.

By performing an intermediate model run that incorporated only the nonpoint source (i.e. WAF) management measures, leaving WWTPs at their "existing" condition, and comparing that to the "TMDL-e" model run, it is possible to estimate the "Nonpoint only" portion of reductions in annual-average concentration and total-annual loading. Figure 9 shows model output profiles that depict this process for two river stations, and also shows the net percent reductions then calculated as being achieved by the WWTP and WAF sources upstream from the stations.

Figure 9 also illustrates an important but sometimes confusing relationship between loading and instream concentrations. When concentration output is reviewed, point source reduction causes the most change. When loading output is reviewed, nonpoint source reduction causes the most change. For the purposes of this TMDL, the most important point to be gained from Figure 9 is that both point (WWTP) and nonpoint (WAF) sources are significant contributors.

Margin of Safety

This TMDL includes an *implicit* margin of safety that is significant but not specifically quantifiable. The margin of safety is embodied in two major aspects of the technical analyses and modeling performed to develop the TMDL.

First, a very large amount of data and information concerning nutrient sources and conditions in the North Bosque River watershed has been collected and assessed. Few watersheds in the United States have been studied as extensively with regard to nutrient issues and agricultural management practices. The data were thoroughly analyzed and peer-reviewed by experienced professionals at TIAER and in the technical work group that assisted in the project. Because of these factors, uncertainty associated with the study conclusions is minimized, and should be significantly less than the uncertainty associated with nutrient loading analyses in general.

Second, the SWAT model used for assessing alternatives is generally conservative. This is evident by comparing the "existing" model scenario output (exceedance probability curves) to the monitored phosphorus data from corresponding stations. Most notably in the lower river stations (i.e. Clifton and Valley Mills), the "existing" model scenario output tends to predict higher annual-average phosphorus concentrations than were recorded during the mid- to late-1990s. The model was calibrated to data from a period that included two major flood events, which probably maximized watershed nonpoint source loading and stream transport of phosphorus to the lower watershed. Since the calibration period, severe drought conditions have occurred, with minimal watershed loading and more loss of stream flow to evaporation or bank storage than the model calibration conditions. So, recently observed river concentrations have been significantly lower than the model predicts would occur. Calibration to maximal loading conditions means that the model tends to overpredict loading and transport under more average or low-flow conditions, and is thus environmentally conservative. Basically, this means that management measures are likely to be more effective, in the long-term average context of TMDL targets, than the model results predict.

Pollutant Load Allocations

TMDLs establish the allowable pollutant loading for each water body, distributed among the source categories that contribute the pollutant. The TMDLs described in this section will result in compliance with water quality standards. Implementation plans to achieve the recommended reductions may select a phased approach that achieves initial loading reductions from a subset of the source categories. A phased approach would allow for development or refinement of technologies that enhance the effectiveness of certain management measures. Periodic and repeated evaluations of the effectiveness of implementation measures will assure that progress is occurring, and may show that the original distribution of loading among sources can be modified to increase efficiency, while maintaining the objective of compliance with water quality standards.

The phosphorus sources addressed by these TMDLs include urban stormwater runoff, municipal wastewater discharges, wood/range land, pasture, non-row crops, row crops, and dairy waste application fields. Estimates of the existing (circa 1997) gross soluble phosphorus loading from each of those source types were derived from land use data, water quality data, phosphorus export coefficients (McFarland and Hauck 1998), and permit records (for municipal wastewater discharges), at several index stations along the North Bosque River (McFarland and Hauck 1999a). Those estimates are presented in Fig. 3, which shows both the percent contribution by each source type, and the total accumulated load during the 29-month monitoring period, by source type.

Those estimates are not directly comparable to the model output values or figures. The gross loading estimates predict how much phosphorus leaves a relatively small site (i.e. per acre) during an average year, and do not account for any loss or assimilation between the source site and the water quality site some distance downstream. Thus the estimates represent the gross average movement of phosphorus within a subwatershed, but stream data would measure the net unassimilated loading that passes the monitoring site (which must always be less than the gross export). However, the percent contributions by source type derived from these estimates can be assumed to be reasonably consistent and applicable to net soluble phosphorus loading. The percentile contributions, together with land use area information, can then be used to determine which subcategories of point and nonpoint sources should be targeted for reduction efforts.

Management measures ultimately implemented as a result of these TMDLs should lead to reducing average total-annual net SRP load by approximately 50%, and average annual-average SRP concentrations by approximately 47%. Stated another way, following implementation of management practices to meet the recommended reductions, the amount of soluble phosphorus that passes Meridian each year should be approximately half as much as would have passed there under similar environmental conditions before TMDL implementation.

Model scenarios represented existing conditions prior to TMDL implementation and predicted future conditions following TMDL implementation. Table 4 summarizes before and after model results, from the "Existing" and "TMDL-e" scenarios respectively, showing predicted average total-annual loading for each of the river index stations. These values represent net loading predicted to pass each site, which is different from (less than) the gross loading generated by sources upstream from the sites.

Table 4. Predicted Net Average Total-Annual Soluble Phosphorus Loading

Loading is expressed in units of kilograms per year, kg/yr	Above Stephenville	Below Stephenville	Above Meridian	Clifton	Valley Mills
Predicted average total-annual load from 'Existing' scenario	4,061	10,068	22,117	26,990	28,832
Predicted average total-annual load from 'TMDL-e' scenario	1,556	4,173	10,479	15,498	17,625

Both point and nonpoint sources are expected to reduce their aggregate (i.e. sum of all individual sources) loading by approximately 50% compared to their respective existing aggregate loading. Table 5 presents estimates of the percent reductions needed above each river index station.

Similar comparison of model simulations indicates that average annual-average SRP concentrations will also be significantly reduced. Table 6 illustrates that overall annual-average concentration reductions ranging from 33% to 61% are predicted by the model, as the average response over multi-year periods, depending on where in the watershed the reductions are calculated. Most of the reduction in annual-average concentration is expected to occur in the middle watershed.

The "preliminary target" established from biological data and analyses was to reduce soluble phosphorus loading above Meridian approximately 50%, in order to attain a similar reduction in annual-average concentration. Tables 4 and 6 show that average total-annual load and average annual-average concentration can both be reduced by approximately 50% at the model output station "Above Meridian," which is the nearest

Table 5. Estimated Gross Loading Reductions Needed To Achieve Target Percentages below are calculated relative to existing gross loading, and estimate the anticipated average % reductions within watersheds where gross loading originates.					
	Above Stephenville	Below Stephenville	Above Meridian	Clifton	Valley Mills
Estimated % reduction of nonpoint source loading	61.68 %	55.31 %	51.50 %	41.10 %	37.54 %
Estimated % reduction of point source loading	0.00 %	66.90 %	62.70 %	57.50 %	50.80 %
The decimal places shown in this table are artifacts of the estimation process, and should not be considered significant.					

Table 6. Average Annual-Average Soluble Phosphorus Concentration					
	Above Stephenville	Below Stephenville	Above Meridian	Clifton	Valley Mills
From 'Existing' scenario (ppb)	203.3	1,143.2	117.0	52.2	41.3
From 'TMDL-e' scenario (ppb)	114.2	448.1	54.5	30.3	27.5
% reduction	43.83 %	60.80 %	53.42 %	41.95 %	33.41 %
The decimal places shown in this table are artifacts of the estimation process, and should not be considered significant.					

to the original monitoring station for which preliminary targets were discussed. This means that the amount of soluble phosphorus that passes Meridian each year after TMDL implementation should be approximately half as much as would have passed there under similar environmental conditions before TMDL implementation.

Some allowance for future growth (AFG) is embodied in these TMDLs. The "future growth" model scenarios incorporated full permitted discharge from WWTPs, the maximum number of dairy cows allowable under current permits and rules with corresponding WAF area, and included a hypothetical 0.6 million gallons per day (MGD) of wastewater discharge to represent potential new industry or municipal growth beyond the capacity of current permits. In addition, the "future" scenarios used human population projections to estimate urban areas 20 years in the future and adjusted urban runoff accordingly. As shown in Figures 4 through 8, TMDL implementation is expected to achieve annual-average SRP concentrations and total-annual net SRP loading that are significantly less than the existing condition, with 20 years of growth and full permitted discharges included.

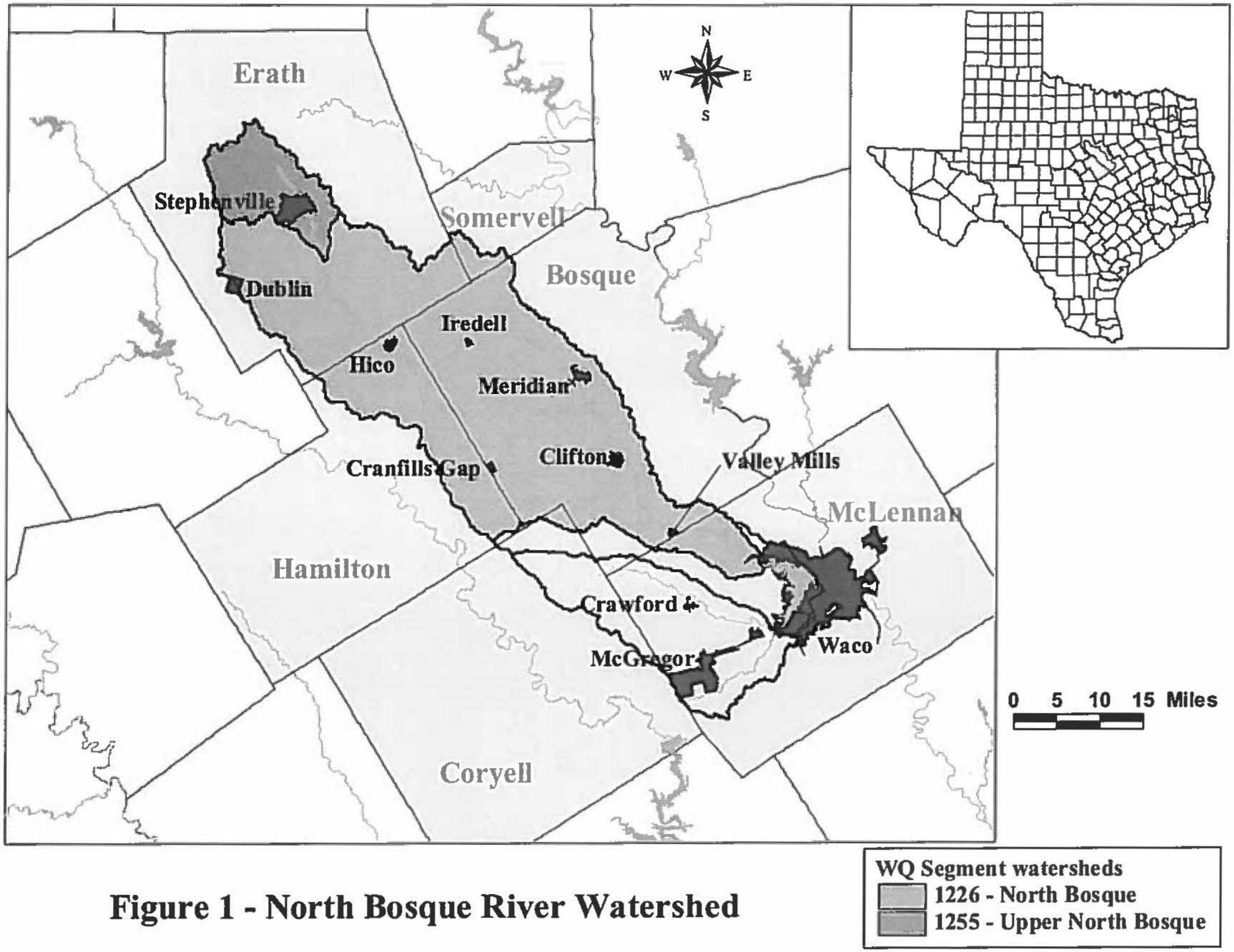
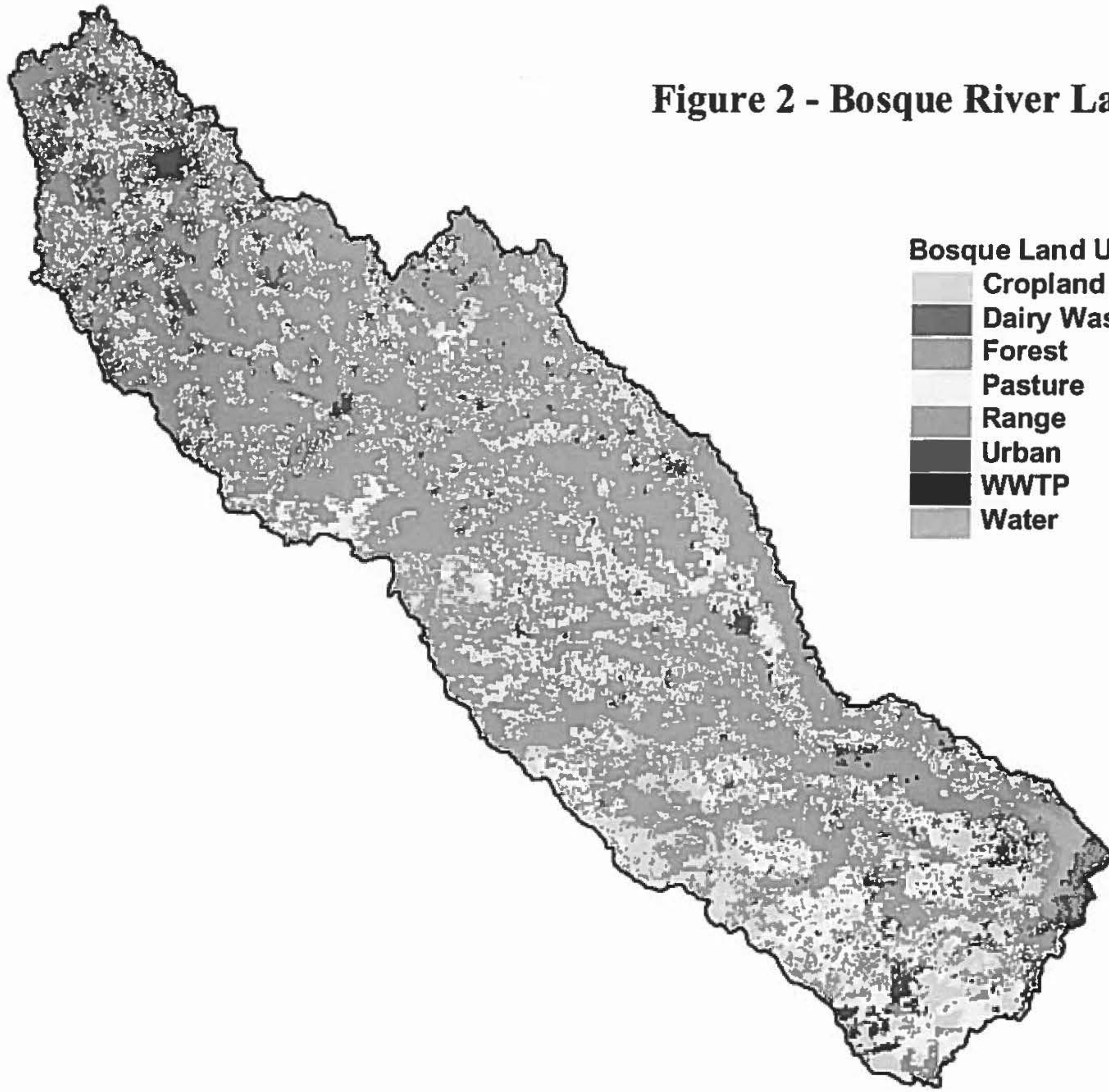
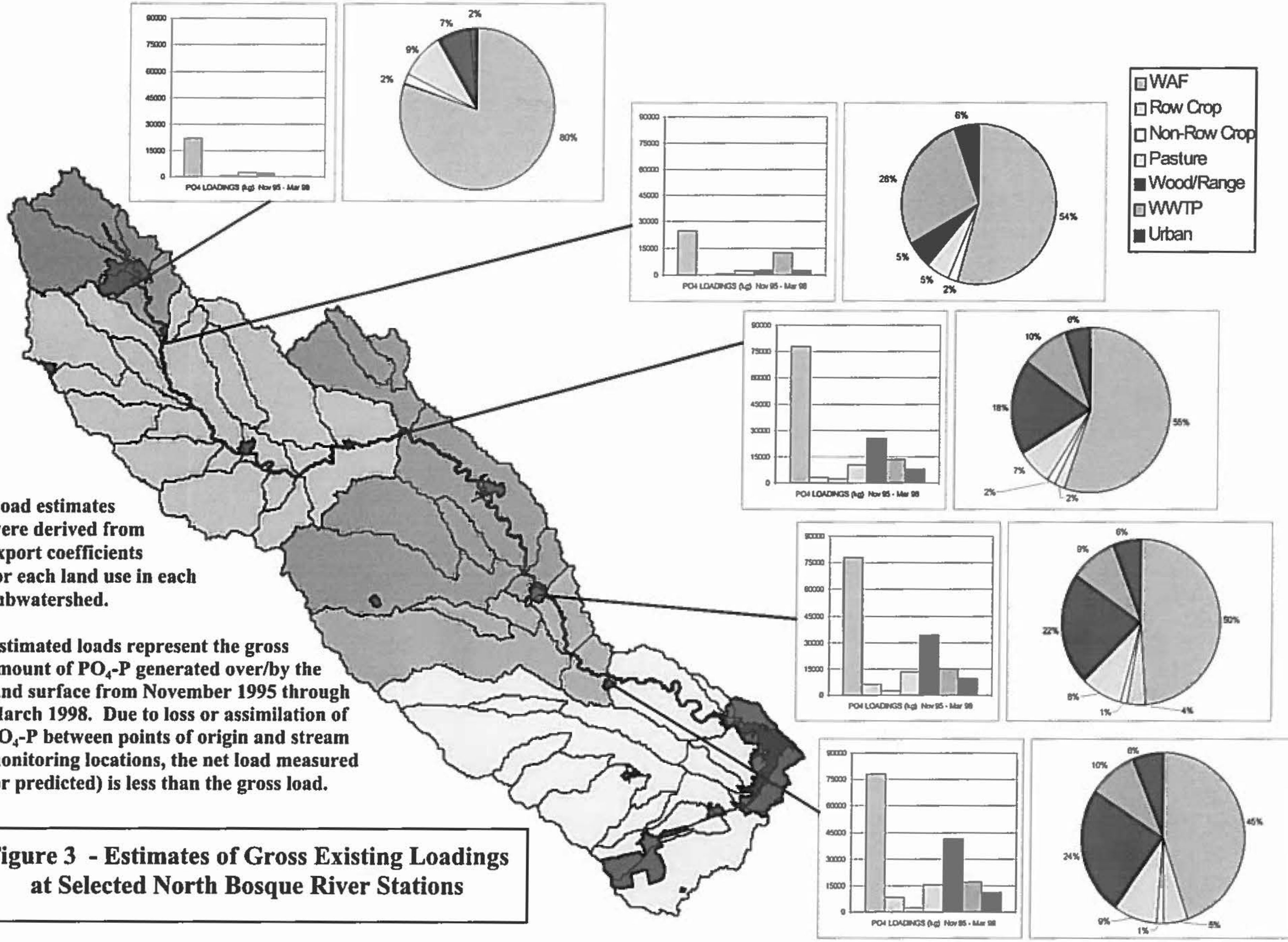


Figure 1 - North Bosque River Watershed

Figure 2 - Bosque River Land Uses





Load estimates were derived from export coefficients for each land use in each subwatershed.

Estimated loads represent the gross amount of PO_4-P generated over/by the land surface from November 1995 through March 1998. Due to loss or assimilation of PO_4-P between points of origin and stream monitoring locations, the net load measured (or predicted) is less than the gross load.

Figure 3 - Estimates of Gross Existing Loadings at Selected North Bosque River Stations

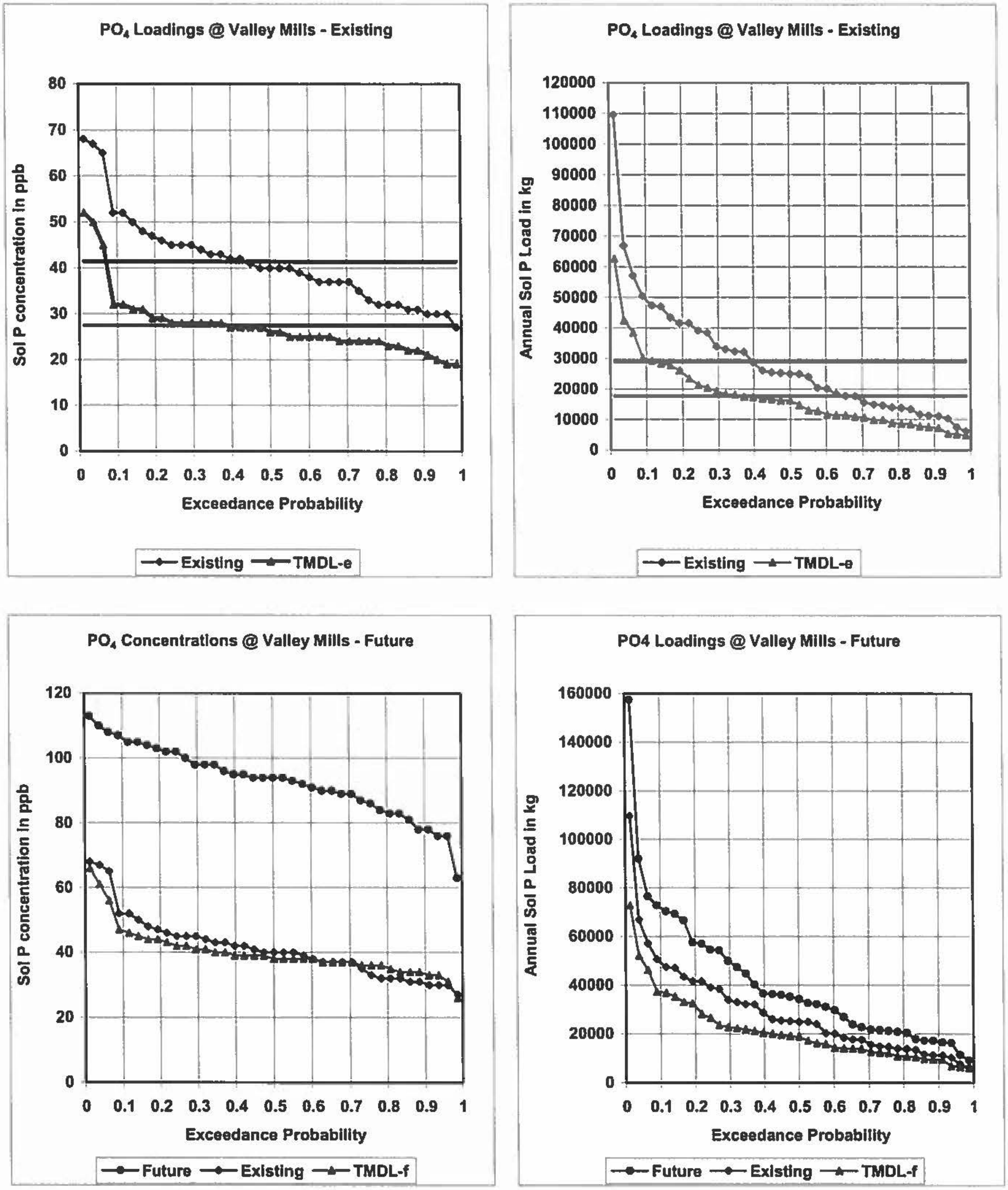


Figure 4 - SWAT Model results at Valley Mills

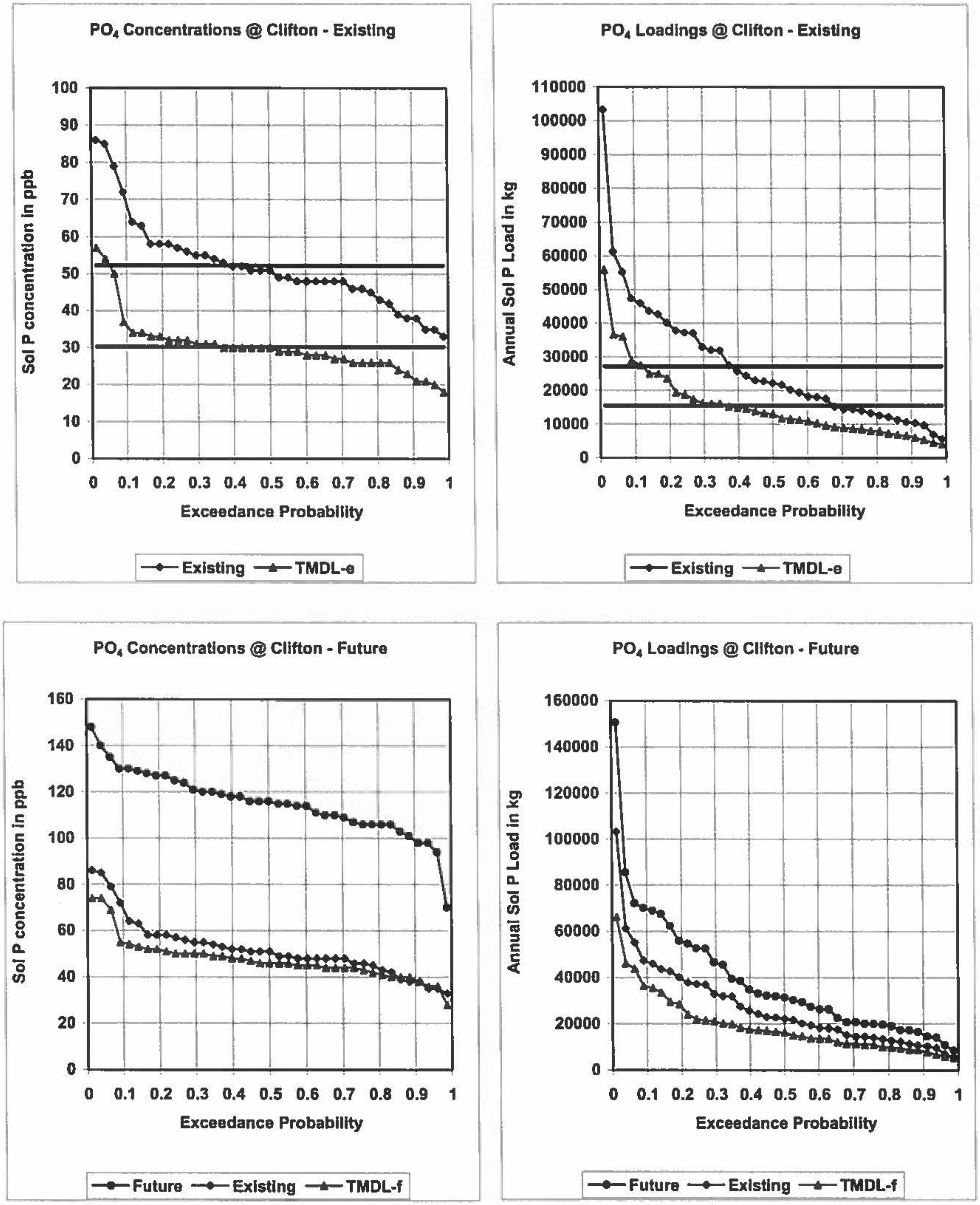


Figure 5 - SWAT Model results at Clifton

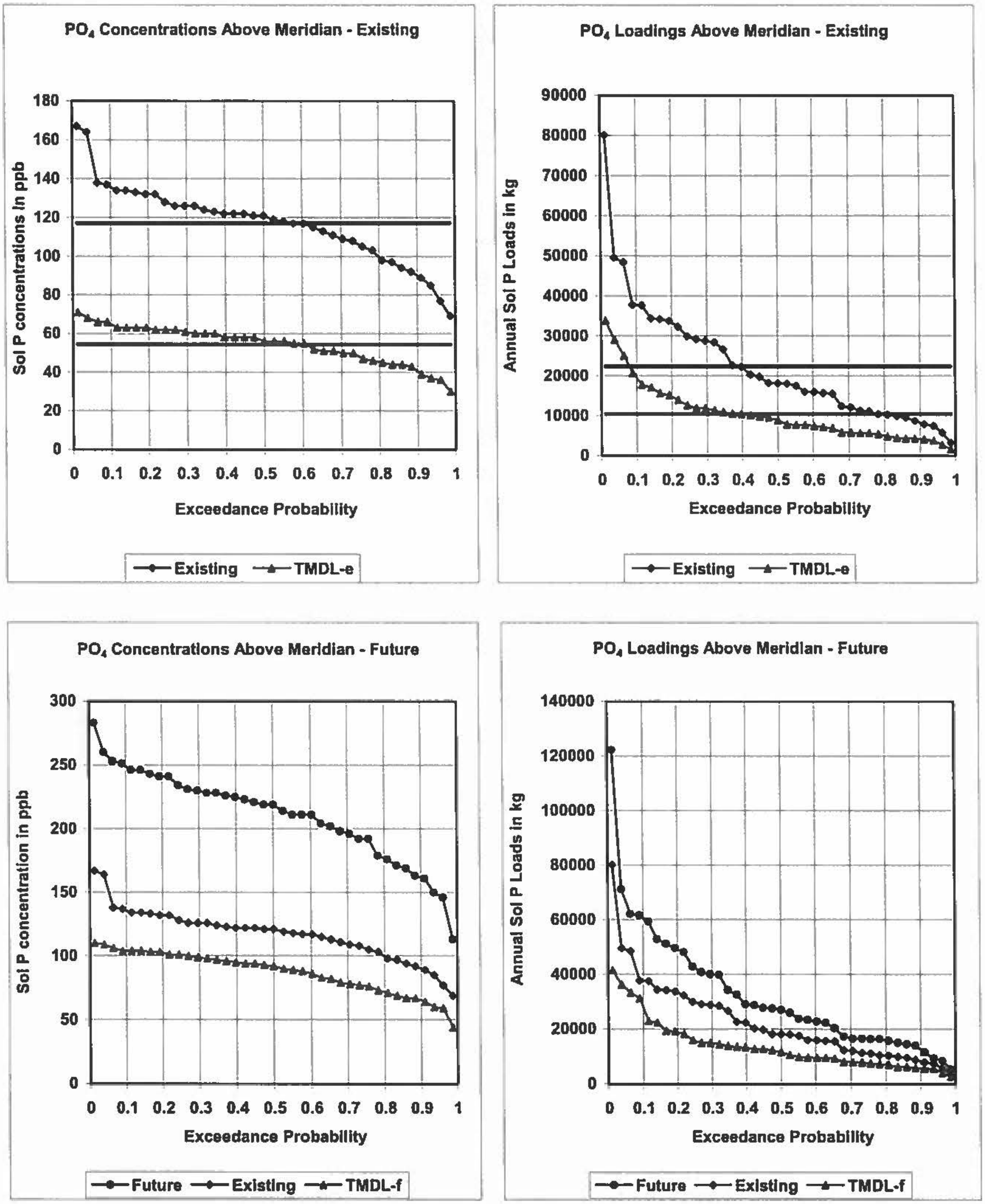


Figure 6 - SWAT Model results Above Meridian

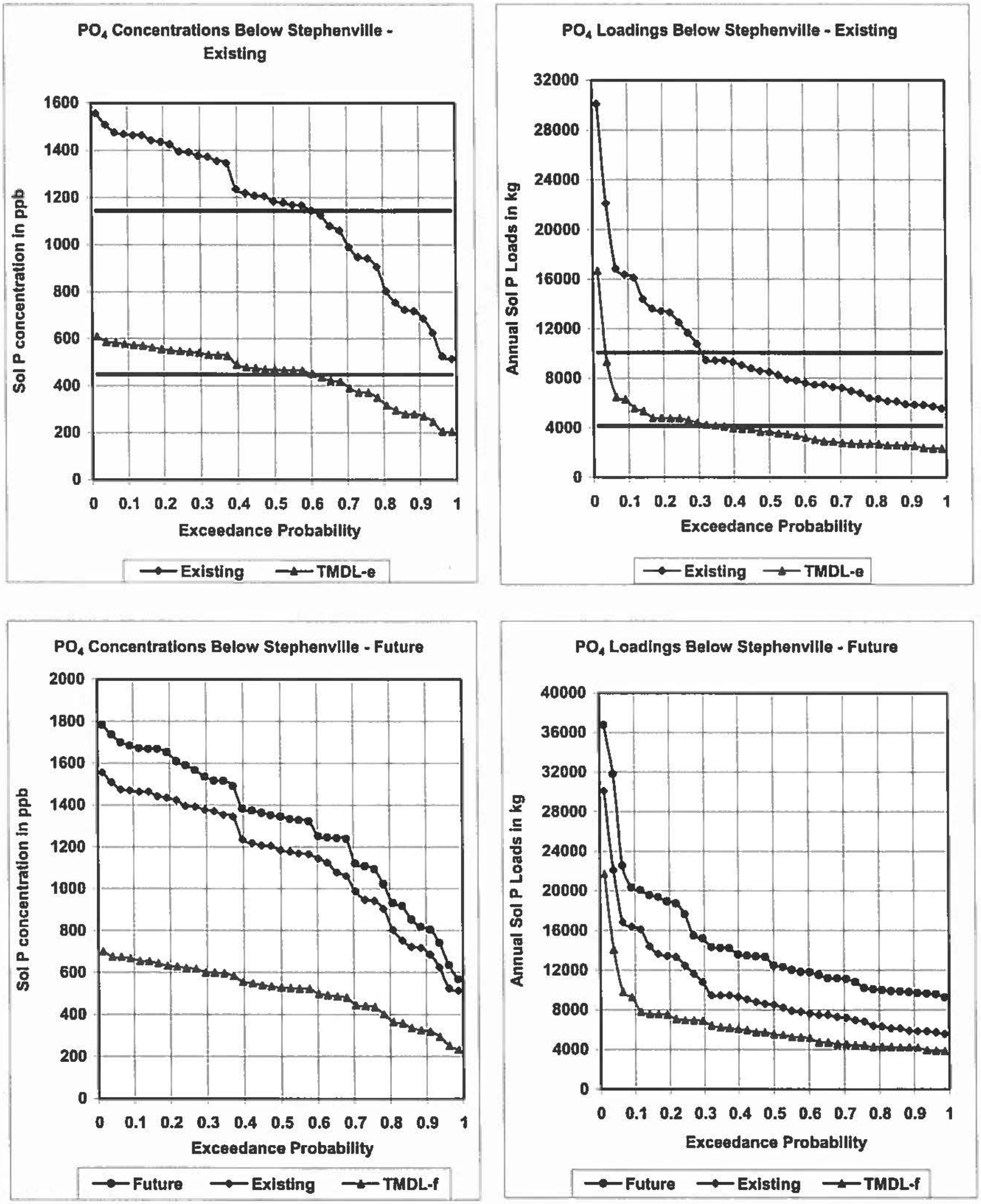


Figure 7 - SWAT Model results Below Stephenville

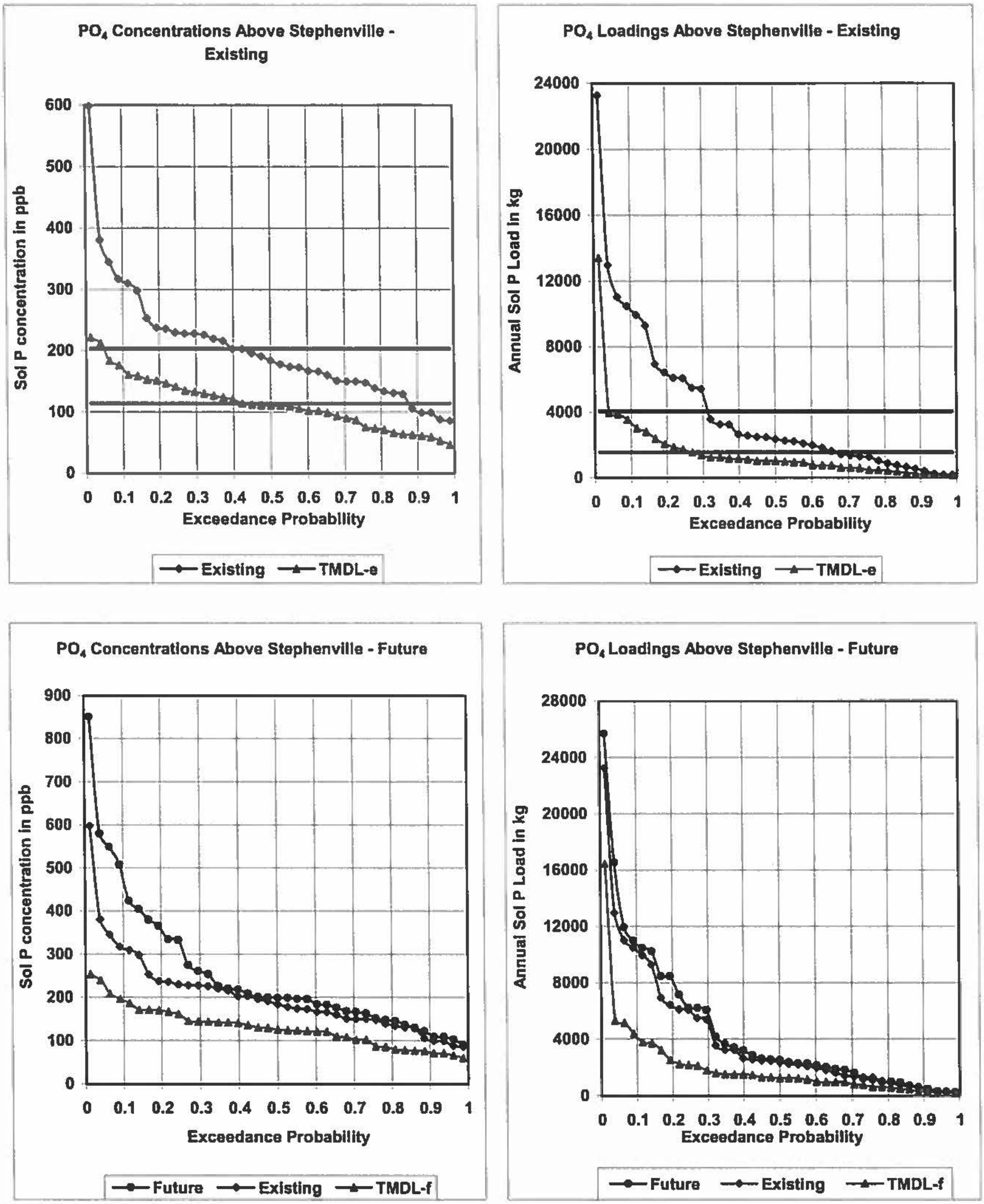


Figure 8 - SWAT Model results Above Stephenville

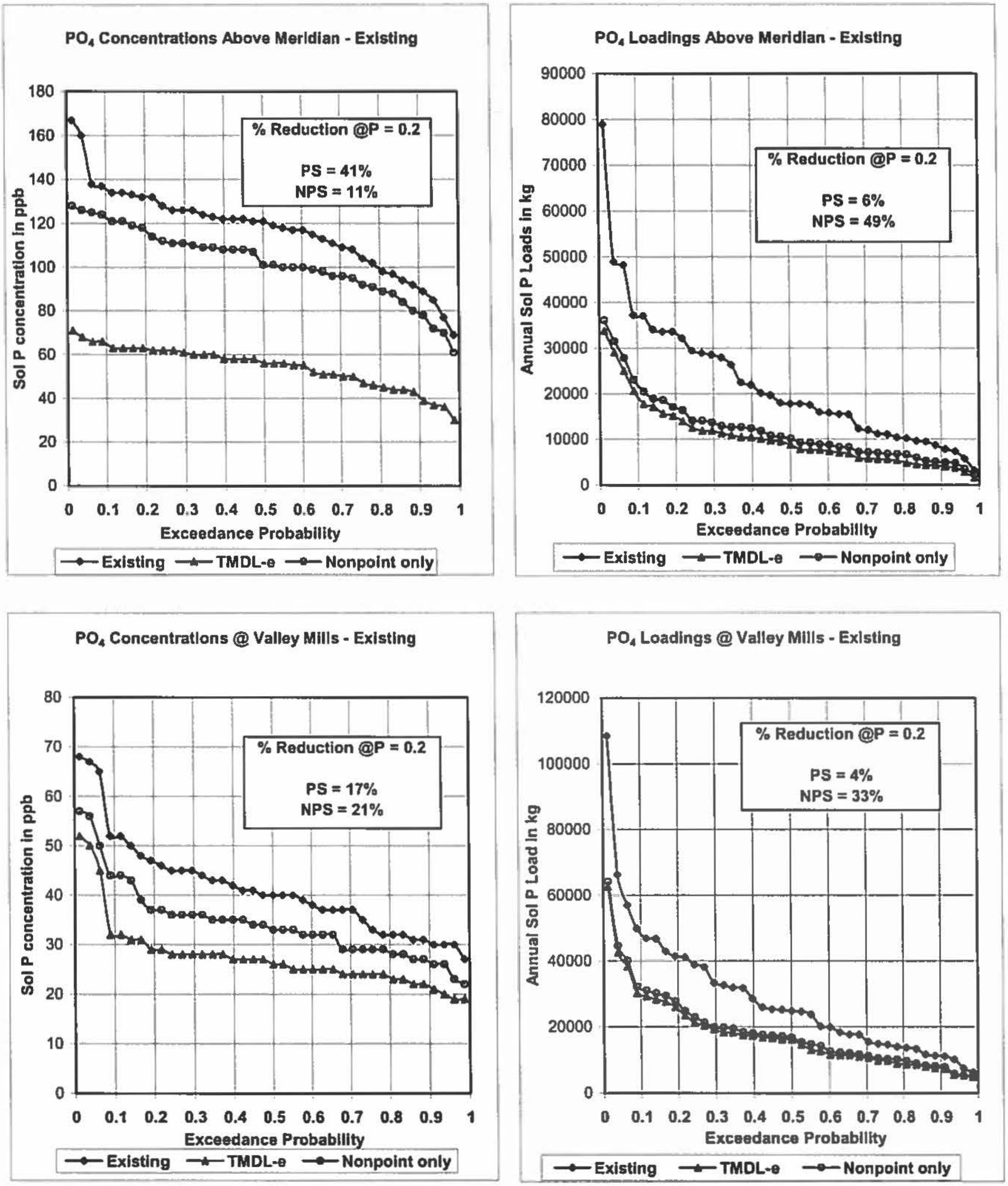


Figure 9 - SWAT Model results for Nonpoint Sources

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