5-2008

Decision Analysis Considering Welfare Impacts in Water Resources Using the Benefit Transfer Approach

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DECISION ANALYSIS CONSIDERING WELFARE IMPACTS IN WATER RESOURCES USING THE BENEFIT TRANSFER APPROACH

by

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A dissertation submitted in partial fulfillment
of the requirements for the degree

of

DOCTOR OF PHILOSOPHY

in

Civil and Environmental Engineering

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UTAH STATE UNIVERSITY
Logan, Utah

2008

ABSTRACT

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Resources Using Benefit Transfer Approach

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Decision making in environmental management is faced with uncertainties associated with related environmental variables and processes. Decision makers are inclined to use resources to acquire better information in one or more uncertain variable(s). Typically, with limited resources available, characterizing the feasibility of such investment is desirable yet complicated.

In the context of reducing inherent uncertainty, decision makers need to tackle two difficult questions, first, the optimal selection of variable(s) and second, the optimal level of information collection which produces maximum gain in benefits.

We develop a new framework to assess the socioeconomic value of potential decisions of collecting additional information for given variable(s) to reduce inherent uncertainty. The suggested framework employs advanced social welfare concepts to facilitate eliciting the social acceptability of decisions to collect better information. The framework produces estimates of changes in utility levels and willingness to pay for target population using the benefit transfer method.

The practicality of the framework is established using the following common problems in the field of water resources: 1) the uncertainty in exposure to health risk due to drinking a groundwater source contaminated with a carcinogen, 2) the uncertainty in non point source pollution loadings due to unknown hydrologic processes variability, and 3) the equity level in allocating mitigation responsibilities among polluters. For the three applications, the social acceptability of potential decisions is expressed in monetary terms which represent an extension on typical cost benefit analysis by including the socioeconomic value of a decision. The specific contribution of this research is a theoretical framework for a detailed preliminary analysis to transform and represent the given problem in useable terms for the social welfare analysis. The practical framework is attractive because it avoids the need to employ prohibitively expensive survey-based contingent valuation methods. Instead, the framework utilizes benefit transfer method, which imposes a theoretical behavioral structure on population characteristics such as age and income and to produce empirical estimates for a new problem setting.

(178 pages)

I cherish the inspiration of my mother and father, wife and daughter, my teachers, and my friends.

This dissertation is dedicated to all of them.

ACKNOWLEDGMENTS

The years I have spent at Utah Water Research Laboratory have been a joyful experience. I have learned a great deal here and I am deeply indebted to many people whom made my life here pleasant.

I would like to express my sincere gratitude to my teacher professor, Jagath Kaluarachchi, for the opportunities that he has made available to me, whose stimulating conversations gave me inspirations, not only to this work, but also to my life in general. I am grateful for the time and energy the members of my research committee, Professors Mac McKee, Wynn Walker, Bruce Bishop, and Gilberto Urroz, have given. I am grateful to the great teachers during my M.S. degree at USU who inspired me to pursue my education. I am indebted to the late Dr. Lyman Willardson whose advice guided me through my career; may his soul rest in peace. I am deeply grateful to my family. The continuous support of my mother Shadia and my father Adel made this journey a success. My lovely wife, Mays, and little angel Lana, and sisters Hala, Heba, and Lina illuminated my life and gave me a strong will to fulfill this work.

Special thanks go to my dear friend and colleague Yasir Kahiel, who offered his generous help at numerous times. Also, thanks to Abedalrazq Khalil, Ibrahim Khadam, Osama Akashe, Kashif Gill, and Khalil Ammar who made my work experience wonderful. Above all, I thank GOD; for it is through Him all things are possible. My life has been truly blessed.

Ashraf A. Shaqadan

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CHAPTER I

INTRODUCTION

General Introduction

In general the decision making process in water resources problems aims to achieve the following goals: (1) reduce the uncertainty level in inputs of a given problem to characterize the damages more accurately and ultimately help reducing the impact on the recipient, and (2) to reach mitigation goals with the least possible cost to the polluters.

In all cases, decisions in water resources management have economic and welfare implications at the community and the individual levels. The typical benefit-cost analysis approach fails to evaluate such impacts which are critical factors to determine sustainability and success of any regulation or policy that affects individuals' welfare.

Uncertainty in environmental system management stems from data scarcity, often manifested as risk to the environment and population (Yokato and Thompson, 2004). The decision-making process must include an assessment of uncertainty. In environmental management problems, reducing uncertainty provides the basis for decision-making under risk, which is translated ultimately to measurable outcomes such as public health and economic consequences. Typically, health or environmental risk due to inputs uncertainty may be large enough to impact the decision-making process. Because resources are scarce and the society has to make choices and spending on additional information should be viewed as a tradeoff problem with other competing needs.

Therefore, the evaluation of welfare benefits of reducing uncertainty through acquiring additional information is a key component of decision-making.

In the context of uncertainty reduction, the value of information analysis (VOI) arises as suitable approach to estimate welfare impact of a considered decision (Mowshowitz, 1991).

The VOI approach estimates the change in expected “utility” as a result of a decision of acquiring additional information in a given uncertain environmental property (Hirshleifer, 1971). In this context, if the social value of information exceeds the costs of its acquisition, it is worth seeking. The VOI analysis approach provides guidance in risk management since it allows reducing uncertainty and therefore the risk by directing information gathering efforts to the most profitable and socially acceptable manner (Yokato and Thompson, 2004).

Protection of groundwater resources from contamination is a major environmental concern due to its impact on public health (Maxwell et al., 1998). Water problems affect many functions of the society including environmental and economic functions. Therefore, a broad view of water quality problems with different types of information needs should be considered. Remediation of polluted groundwater resources requires Long Term Monitoring (LTM) to characterize and track plume migration. Plume characterization involves the use of spatially dispersed measurements of contaminant concentrations at critical locations of the domain where no prior measurements are available. The typical goal of LTM is to provide sufficient number of samples to characterize the plume at all times with acceptable confidence. Besides the high costs of well installation, sampling and maintenance, the non-traditional benefits of LTM such as as protecting groundwater resources and individuals' health requires an approach that extends beyond typical benefit-cost analysis to elicit societal value for this kind of benefits.

An additional challenge to water resources management is the Non-Point Source pollution (NPS) of water bodies. Water quality problems remain a challenge in many regions of the nation (US EPA, 2002). Nutrient rich runoff is the most widespread pollution source; it affects about half of the impaired lake areas and about 60% of the impaired river reaches (Carpenter et al., 1998). The increased loading of nutrients causes eutrophication of water bodies which degrades the health of fish habitats, and even increases water treatment costs (US EPA, 2003; Poor et al., 2001). In NPS pollution management; decisions are based on water quality sampling programs with various spatial and temporal resolutions. Typically, decision-makers observe random signals of nutrient loading to a water body at discrete points in time at a given sampling interval. The discrete data points are used to estimate the annual NPS pollutant loadings which provide the basis for policy evaluation. In the context of data collection; an assumption of constancy is implied where stability in pollutant releases between samplings is assumed to validate the annual loading estimates. This assumption overlooks the impact of hydrologic variability and introduces uncertainty in pollutant loading estimations. This uncertainty imposes negative effects on mitigation efforts. Decision-makers tend to relate observed pollution to land use practices which translates to additional restrictions on the economic productivity of stakeholders due to misidentification of pollution sources. In this sense, the benefit of reducing uncertainty in NPS loading is two-fold: 1) it protects producers from additional economic losses due to imposing of costly overprotective measures and 2) it protects against unexpected shock loads which cause unwanted consequences on related recreational activities such as fishing.

Another persisting challenge to NPS pollution management is the issue of justice and social acceptability of NPS pollution reduction regulations such as TMDL. The TMDL application produces economic costs to polluters, therefore, the economically efficient allocation scheme is typically sought to minimize the overall cost of pollution control. The allocation of pollution control responsibilities among suspected parties is challenging due to the uncertainty associated with identifying the contribution of each source to the total load. For a pollution control policy to be successful, it has to be socially acceptable by polluters. The social attitude towards the TMDL process has received researchers' attention and several social acceptability measures are now investigated to alleviate some of these adverse effects (Chavas, 1994). As the TMDL application is becoming common across the US; its undesired social impacts such as inequitable allocation of mitigation responsibilities become more visible.

The uncertainty in TMDL application is attributed to the difficulty of characterizing causal relationships between sources and observed pollution levels at the downstream due to the extensive information required to describe key processes such as the fate and transport, and hydrologic factors.

The assessment of the socioeconomic impacts in water resources management decisions require using Contingent Valuation Methods (CVM) that are suitable for valuation of social non-market commodities. Today, most used CVMs are survey based and applied in a local and non-transferable manner to new setting. Assessment of social impacts using survey based CVMs is inherently difficult and often not feasible.

Research Objectives

The goal of this dissertation is to enhance the typical benefit-cost analysis framework to assess societal value of decisions in water resources management. A framework is developed to enhance the decision-making process by incorporating value of information, utility, and willingness-to-pay (WTP) such that a socioeconomic cost-benefit analysis can be used for policy evaluation.

The research objectives are:

1. To develop a theoretical framework to estimate societal value of related input variables of a given problem. To develop the framework we will review the welfare assessment literature to elicit appropriate welfare concepts and measures and will select suitable econometric methods to link the state of the environment with social welfare measures such as utility and willingness-to-pay (WTP).

2. To demonstrate the methodology applicability to common water resources applications. The selected applications involve assessment of related non-market commodities such as uncertainty in contaminated groundwater assessment, health risk, and pollutants loading to surface water bodies, and social acceptability of cost sharing policies. For each application, a detailed practical framework is constructed and illustrated using example calculations.

Research Motivations

Stakeholders and decision makers in water resources are often faced with the need to perform benefit- cost analysis of alternative decisions to achieve an optimal outcome.

Decisions in the field of water resources management have significant welfare implications on affected population which is often ignored in typical cost benefit analysis due to the lack of feasible and practical assessment methods.

This dissertation develops an extended benefit cost analysis framework that integrates welfare impacts in typical problems in water resources management.

Research Contributions

In general, this work addresses the problem of lack of feasible approach to estimate welfare impacts of decisions in water resources management.

The specific technical contributions of this work are to expand benefit cost analysis by developing multi-disciplinary framework to quantify the welfare impacts in the following applications:

First, reducing uncertainty in groundwater pollution management.

Second, reducing risk of NPS pollution loadings due to uncertainty in hydrologic variability.

Finally, estimating social acceptability of cost-sharing pollution reduction regulations.

The integration of welfare impacts in benefit cost analysis is complicated. Therefore, the contribution of this dissertation is to develop the practical framework for selected applications in water resources. The selected applications are thoroughly discussed in terms of constructing the practical analysis framework and populating its components. During this process, several fields of research such as health risk and social welfare assessment are investigated and utilized.

Dissertation Organization

This work is organized to represent the framework development process, consideration, virtues and limitations, and the practical implementation for each of the three applications in water resources management. Chapters I introduces the research and provide justification, and background about the research area.

Chapter II provides a review of the related literature and describes the general concepts of value of information and non-market valuation methods.

Chapter III presents the general framework that is considered to develop specific analysis framework for each application.

Chapter IV details the specific framework development and application for reducing uncertainty in groundwater contamination due to unknown subsurface heterogeneity.

Chapter V details the specific framework development and application to reducing error in NPS pollution loading due to hydrologic variability.

Chapter VI details the extended framework development and application to integrate social acceptability in watershed level NPS pollution reduction regulation.

Chapter VII summarizes the findings of the research, describes the limitations and presents conclusions and recommendations.

CHAPTER II

LITERATURE REVIEW

Introduction

This chapter reviews the basic concepts of the tools used to develop the research components of this dissertation. The Value Of Information (VOI) is the underlying principle to assess benefits of improved information collection to reduce health risk and error in pollution loading estimation in the first and the second applications. A major component of this work is selecting appropriate economic valuation method to quantify welfare impact of alternative decisions in the three applications. Therefore economic valuation methods are reviewed in this chapter.

Value of Information

The general framework of VOI is utilized in the context of uncertainty reduction in environmental parameters such as soil hydraulic conductivity and the amount of pollution generation from watersheds by considering alternative decisions for better information collection scenarios. Individuals may be willing to pay for information depending on the uncertain, and on what is at stake. They may be willing to pay for additional data or improved information as long as the expected gain exceeds the cost of information. In an expected utility maximization framework, VOI represents the difference between the expected utility of the optimal action given information available prior to collecting additional information assuming a linear or exponential utility function and a risk-neutral decision-maker. A VOI analysis identifies the best information collection strategy as the one that yields the greatest net benefit.

The general framework to assess VOI is described in several studies in the literature (Ward, Loftis, and McBride, 1986; Yokota and Thompson, 2004). In the context of uncertainty, we adopted the general framework described by Yokota and Thompson (2004). The expected value of information depends on the set of alternative actions, **a**, and on the benefit gained from adopting action **a** expressed using a set of uncertain parameter, **s**.

Let **u(a, s)** denote the utility or welfare that results from choosing decision **a**. The expected value of perfect information (EVPI) represents the value of eliminating uncertainty fully (i.e., collecting information with perfect accuracy). Due to the impossibility of obtaining perfect information, realistic measures can be used; such as the expected value of sample information (EVSI). The EVSI evaluates the impact of given incremental information improvements which is defined as

$$EVSI = \max\left[u(a_1, s_1)\right] - \max\left[u(a_0, s_0)\right] \tag{1}$$

where u represents utility. The first term represents the maximum utility due to the better information decision scenario (**a**) which updates the parameter state to from s_0 to s_1 (less uncertainty). The second term represents the expected utility associated with the base level of information.

Typically, a VOI analysis involves modeling the available set of actions, prior beliefs about the uncertain inputs and about the accuracy of information collected, the consequences of actions given the true value of uncertain inputs, and the decision-maker's preferences. The prior belief about the uncertain inputs and the accuracy of information collected must be characterized using probability distributions or empirical distribution functions. The analysis must quantify relevant consequences of actions from the perspective of the decision-maker and the monetary outcomes using a common metric (i.e. WTP in the context of VOI).

A relevant issue is the marginal value of improvements in the accuracy of predictions. A greater accuracy generally increases the gain in welfare, but often at a decreasing rate. Also, different levels of accuracy have different values to different users. Thus, from an economic impact perspective, there exists a set of optimal levels of accuracy that balances the value of a forecast with the cost of obtaining that level of improved accuracy.

Concerns about the value of information or data worth are common in the literature (Borisova et al., 2005). Therefore, there is a need to assess the value of information for a given set of data before additional data are collected. A data worth analysis may provide guidance in risk management since it allows reducing uncertainty and therefore the risk by directing information gathering efforts to the most profitable and socially acceptable manner.

Benefit Transfer Approach

Economic valuation deals with the monetary estimation of non-traditional commodities that provide some welfare or utility for people and are not traded on markets. Different from normal commodities where prices indicate the demand on goods, non-market goods are not traded and do not have market prices. The Dupuit-Marshall concept of economic value applies to such non-market commodities (Gowdy and Mayumi, 2001). The Dupuit-Marshall concept suggests that non-market commodities can be metered as the economic value of satisfaction from the item as the monetary amount which the person would be willing to exchange for the item if it is possible to make such an exchange.

Contingent valuation methods are classified into *revealed preference*, where valuations are inferred from actual observations of choice behavior, and *stated preference*, where valuations are directly obtained from hypothetical statements of choice (Kolstad, 2004). The *revealed preference* methods include Hedonic pricing and Travel Cost methods. The *stated preference* methods entails presenting people with a hypothetical contingency scenario and are asked explicitly for what improved water quality is worth to them. The stated and revealed preference methods are acknowledged non-market techniques by the US federal agencies for conducting benefit/cost analysis and for environmental resources analysis (Loomis, 1996). Most CVM studies are costly which makes using CVM studies frequently unfeasible. A more efficient alternative is to use estimates from a study performed in a particular location to derive the benefits in a new location (Desvousges et al., 1992) which is referred in the economic literature as the *Benefit Transfer Method* (BTM).

Economic valuation using traditional CVMs is the “first-best” strategy in which needed information is collected. However, when primary research is not feasible, then the BTM emerges as a “second-best” strategy to evaluate management and policy impacts.

The BTM is attractive compared to traditional CVMs because it does not require expensive and lengthy data collection (Desvouesges et al., 1992; Brouwer, 2000). The benefit transfer can be conducted in two modes: (1) direct values transfer of estimates, and (2) the benefit function transfer (Smith et al., 2000). The first method applies the benefit estimate directly to the new study site. In the second method, the estimated benefits are estimated through a derived function that uses relevant local data sources (i.e. census data). Using a derived benefit function has the advantage of allowing adjustment of previous estimates for the new site (Loomis, 1996).

In this work, a structural meta-analysis approach is used to apply the BTM. A meta analysis approach utilizes theoretically sound systematic framework and uses estimates reported in the related literature (Pattanayak, Smith, and Van Houtven, 2004). A meta-analysis utilize disparate quantitative literature of the same commodity (e.g. different sampling intervals), and generates a benefits transfer function or a prediction formula (Pattanayak, Smith, and Van Houtven, 2004). A meta analysis is attractive compared to the conventional survey-based data intensive contingent valuation methods. In addition to the significant labor and time investment, the CVMs are only valid locally which make it a less attractive option.

In economic analysis, the prohibitive cost and time requirements for social preference studies justifies the use of benefits transfer approach in which the benefit estimates (e.g., willingness to pay) derived from one population are transferred to a new population in a different context. Benefit transfer provides a feasible approach to assess anticipated benefits of proposed measures; yet this approach has been criticized for lacking a well-defined theoretical foundation.

CHAPTER III

GENERAL FRAMEWORK

In this chapter the general methodology used to develop practical framework for the different applications is presented here.

A basic assumption in this work is constructed in light of the VOI approach where an improved decision due to better information has a social value that can be quantified. For convince, the general framework is divided into three modules, illustrated in Figure 1: (1) additional data selection and realization; (2) characterization of additional data impacts, and (3) welfare and socioeconomic analysis. The application of these modules requires a carefully planned preliminary analysis for a given problem.

The first module involves analyzing the problem to select an appropriate environmental parameter with the capacity of representing a set of information levels. The second module involves the assessment of environmental impacts of the target parameter with different information levels. The environmental impact type is determined by the parameter and the problem settings.

The first two modules are necessary as a preparation for the socioeconomic analysis listed in the third module which is the major contribution of this research to the field of environmental decision-making.

The third module represents the socioeconomic and welfare analysis which is based on other literature applying BTM and revised here to address incremental improvements of selected indicator in environmental management.

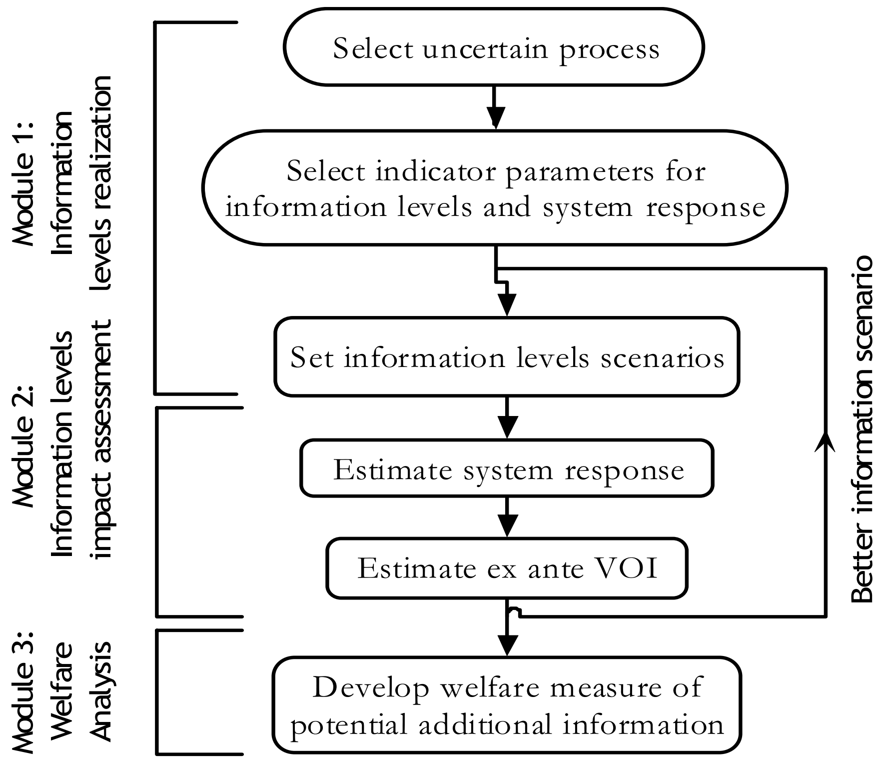

Figure 1. Schematic of the proposed generic framework of this study.

CHAPTER IV

STRUCTURAL BENEFIT TRANSFER FOR INCREMENTAL UNCERTAINTY REDUCTIONS IN THE MONITORING OF CONTAMINATED GROUNDWATER

Management of contaminated groundwater resources is difficult due to limited resources available to monitor and remediate a large number of contaminated sites. Earlier research recognized the negative impacts of spatial data scarcity on the success of groundwater monitoring and remediation plans. Therefore, an important question is how to allocate limited resources to collect additional information to better estimate the risks and remediation priorities versus the willingness to pay by the society. This paper introduces one of the few applications of structural benefit transfer to quantify welfare impacts of improving groundwater monitoring in terms of willingness-to-pay (WTP).

This work extends the earlier studies on health risk assessment methodology and introduces a practical socioeconomic framework to estimate individuals' WTP for a proposed improvement in data gathering. The methodology analyzes scenarios of different reductions in subsurface heterogeneity by collecting additional spatial data to reduce hidden health risk of a target population and computes the health-economic impact as an estimate of the individual and aggregate WTP. The variability of characteristics of the target population is represented through probabilistic distributions of income, health state, age, and risk exposure parameters. The methodology produces predictions of WTP that are consistent with the patterns described in the economic theory and literature.

Introduction

Overview

The accurate monitoring of contaminated groundwater resources has been difficult because of the limited resources available, uncertainty arising from complexities of contaminants and media characteristics, and the presence of many large-scale polluted sites (Ward, Loftis, and McBride, 1986). Water quality problems affect many functions of society including environmental, economical, and ecological functions. Contaminated groundwater has effects on the population that ranges from direct health effects such as morbidity and mortality to indirect economic damages such as restrictions on recreational uses (Maxwell et al., 1998).

Assessment of environmental and economic impacts of contaminated groundwater on a population is complex (Zhao and Kaluarachchi, 2002). Therefore, addressing water quality problems calls for a broad view that utilizes several types of data for various uncertain variables and processes.

Limited resources is a constraint for most contaminated sites listed in the National Priority List because these sites typically need millions of dollars per site and can take many decades to remediate. Stakeholders need a management tool to help guide allocation of resources to reduce overall uncertainty in the most profitable way.
In groundwater contamination, uncertainty translates to tangible outcomes such as exposure to unseen (hidden) health risks inherited due to uncertain input variables.

Logically, a decision that reduces uncertainty in groundwater contamination has social benefits including reductions in exposure to hidden health risk and the associated economic losses due to expected illness or mortality. In summary, there is a need to evaluate the socioeconomic benefits of a potential decision of improved monitoring by evaluating the welfare impact of uncertainty reducing decision. The quantification of welfare impacts of such decisions in monetary terms is complicated task especially under the time constraints for decision making.

Subsurface heterogeneity observed in large aquifer systems is an important characteristic that needs to be properly described to predict the fate and transport of contaminants in groundwater. It is almost impossible to gather adequate information to clearly describe the spatial structure of heterogeneity. In this context, most data gathering and monitoring networks (MN) are designed under optimal conditions to describe subsurface heterogeneity with available resources while attempting to address the most critical site-specific questions.

Numerous studies successfully tackled several aspects of subsurface heterogeneity. For instance, Tompson, Ababou and Gelhar (1989) and Tompson and Gelhar (1990) focused on improving the simulation techniques of aquifer heterogeneity, while Maxwell et al. (1998) and Maxwell and Kastenberg (1999) developed a framework to estimate health risk impacts for uncertainty in subsurface heterogeneity. Therefore, developing a practical approach to quantify the welfare impacts of changes in expected exposure levels to health risk is a natural improvement. Given the financial and time constraints for decision valuation, conventional contingent valuation methods are not feasible and non-traditional methods are needed.

In essence, there is a need to develop a practical methodology to evaluate the welfare impact of reduction in health risk due to improved data collection and the willingness-to-pay (WTP) by population at risk based on their socioeconomic conditions (Abdalla, Roach, and Epp, 1992). The goal of this work is to address this deficiency in research by using a socioeconomic analysis of monitoring groundwater contamination to define how the society values information in reducing public health risks.

Welfare measures for health risk reduction

Numerous studies investigated the valuation of health risk reduction in air and water quality applications. The essence of these studies is to adopt relevant measures of adverse health or environmental effects of expected exposure levels estimated using available information for a given contaminant. A potential decision is deemed feasible if it reduces risk or produces more accurate characterization of actual exposure levels which indicates a positive welfare impact to the target population assuming that only identified risks are mitigated and unidentified risks poses a threat to the population. Economic literature provides a range of classical methods and techniques with varying complexities to quantify the welfare levels expressed in several types of measures.

Valuation methods of welfare impacts are classified into revealed preference, where valuations are inferred from actual observations of choice behavior, and stated preference, where valuations are directly obtained from hypothetical statements of choice (Kolstad, 2004). The revealed preference methods include Hedonic pricing and Travel Cost methods. The stated preference methods include survey method in which people are presented with a hypothetical contingency scenario and are asked explicitly about the scenario, such as what improved water quality is worth to them. The described valuation methods are established non-market techniques used by governmental agencies for conducting benefit-cost analysis and for environmental resource allocation (Loomis, 1996); however, their wide application is limited by monetary and time constraints.

Therefore, an alternative practical economic valuation method such as the Benefit Transfer Method (BTM) is needed. The premise of the BTM is to transfer an established welfare estimate from a study performed at a particular location to derive welfare impacts at a new location in different settings (Johnston et al., 2005). The BTM provides a systematic framework for utilizing existing welfare estimates to produce new estimates for a new similar case (Florax, Travisi, and NijKamp, 2005; Pattanayak, Smith, and Van Houtven, 2004; Smith, Van Houtven, and Pattanayak, 2006). Due to its high practicality and feasibility compared to a typical CVM; the BTM is increasingly used in environmental management studies (Rosenberger and Loomis, 2000; Florax, Travisi, and NijKamp, 2005).

In health risk assessment, the Value of a Statistical Life (VSL) is a commonly used metric that measures the welfare impact of risk reduction assuming that the society accepts a certain monetary value for human life (Viscusi and Aldy, 2003). The US Environmental Protection Agency (US EPA) guidelines recommend a range of VSL values to estimate benefits of reducing health risk in a benefit-cost analysis (US EPA, 2004). There seems to be no universally agreed estimate of the value of a statistical life for benefit-cost analysis in environmental regulations. For instance, while the US EPA guidelines suggest a VSL of about \$5.5 million in 1990 dollars (Dockins et al., 2004), hedonic wage studies use a VSL ranging from \$1 million (Cameron and DeShazo, 2004) to \$10 million (Viscusi and Aldy, 2003).

A major criticism to the VSL is the lack of sensitivity to individuals' characteristics that affects the person's monetary evaluation (Cameron and De Shazo, 2004; Aldy and Viscusi, 2007). Johansson (2002) and Aldy and Viscusi (2007) observed that VSL studies show an "inverted U-shape" pattern with age where the VSL peaks around the age of 40 years.

To summarize, considering the VSL as a welfare measure of risk reduction is not appropriate for this study. To illustrate, if the WTP for risk reduction for saving 1 out of 100,000 lives is $a, then the value of a statistical life is 100,000 x a dollars. Therefore, to preserve individual variability using the WTP is a better measure than the VSL.

However, the benefit transfer approach requires using established WTP or VSL estimates as an input to calibrate the parameters of the benefit transfer model in order to produce new WTP estimates for a new risk reduction setting.

Methodology

Stakeholders desire to estimate a monetary value of the gain in population welfare due to a decision of better information compared to a base case of information collection. This research work is aimed at developing a methodology in which the additional information about uncertainty provides welfare improvement due to more accurate characterization of exposure to risk. In this study, we propose a modulus interdisciplinary framework that spans across the fields of fate and transport of contaminants, health risk assessment, social welfare analysis, and health economics.

The proposed framework links potential decisions of additional data collection to their welfare benefit through the change in expected exposure to health risk determined by improved information. The proposed methodology represents a contribution to the risk-based decision analysis literature due to its unique capacity to elicit a monetary value of welfare benefit produced by a given decision.

The proposed framework is composed of three modules as shown in Figure 2 and these are (1) additional data selection and realization; (2) characterization of additional data impacts, and (3) economic and welfare analysis. The methodology and the application are for monitoring of a groundwater aquifer contaminated with a point-source of carcinogenic contaminant.

The first and second modules adopt the approach of Maxwell et al. (1998) and Maxwell and Kastenberg (1999). The last module is the economic and welfare analysis which is based on the work of Pattanayak, Smith, and Van Houtven (2004) and revised here to address decisions of incremental risk reduction and society's WTP in environmental management.

Module 1: Additional data selection and realization

In groundwater contamination, the subsurface heterogeneity is described by the spatial distribution of hydraulic conductivity (K) which is considered to be spatially correlated random variable in heterogeneous porous media (Dagan and Fiori, 1997; Maxwell et al., 1998). Also, the design of groundwater MN is based on the spatial structure of K . For contaminated aquifers, the extent of spatial data collection is correlated to the assumed spatial K structure.

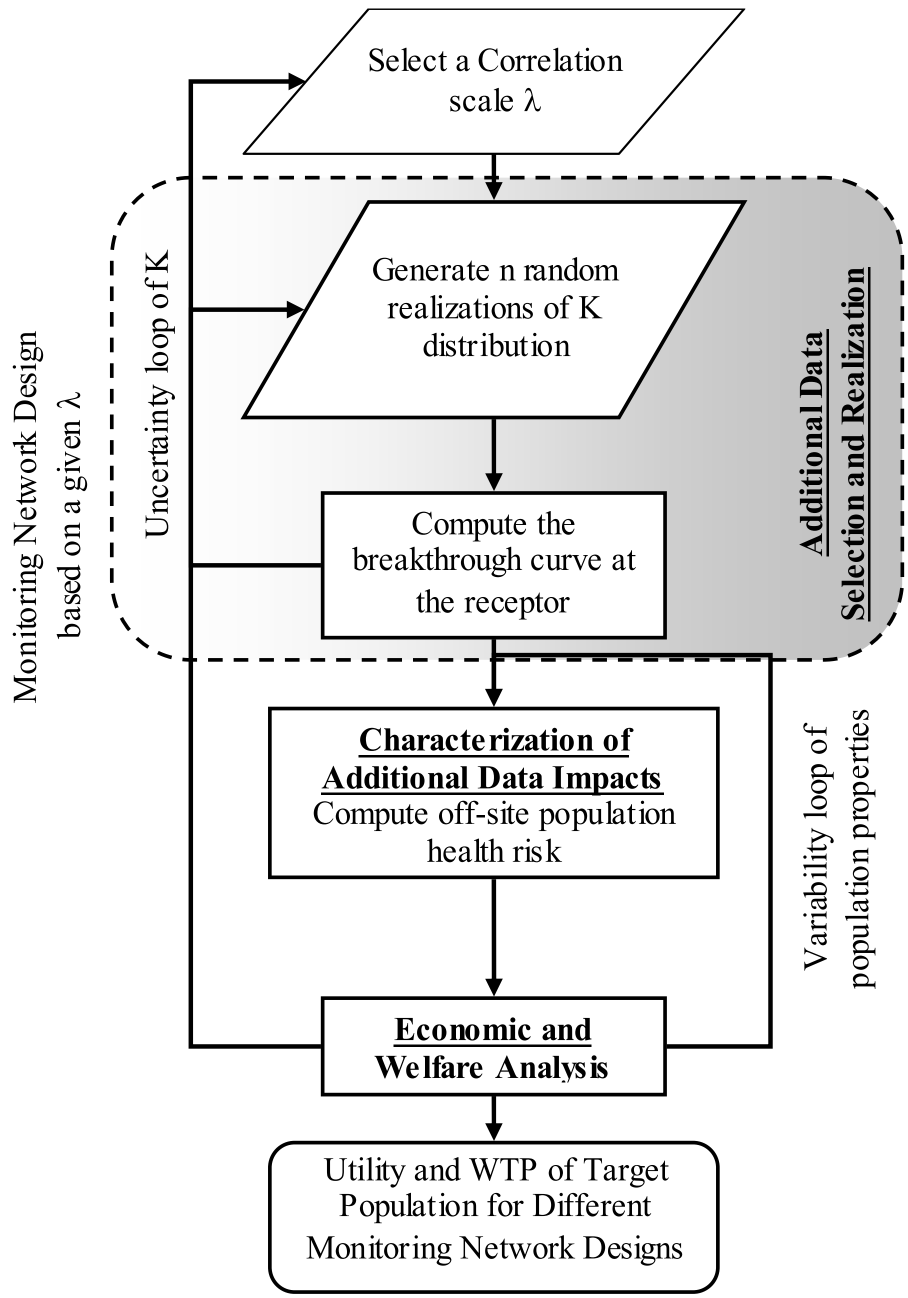

Figure 2. A flow chart of the proposed methodology to compute utility and WTP for a given health risk reduction by additional data collection using nested Monte Carlo method.

Therefore, to achieve accurate predictions of plume migration and relevant mitigation strategies, an accurate assessment of spatial K structure is desired.

The goal of this module is to simulate scenarios of different data availability in a related system variable which is the subsurface heterogeneity. Typically, in groundwater contamination a range of subsurface heterogeneity levels are simulated by varying the K spatial correlation length (λ) which produces variable K spatial structures (K fields). This simulation is performed using Monte Carlo sampling method to produce different series of n equally likely, two-dimensional random distributions of K fields related to different correlation lengths (λ).

For each λ, the set of generated random K fields hereafter referred to as ensemble are utilized in the groundwater movement and contaminant fate and transport simulation to produce breakthrough concentration predicted at the receptor. Next, the maximum 30 yr-average concentration for each K field of an ensemble is used to construct a probabilistic distribution of expected concentration that is unique for a given ensemble.

Since ensembles are generated for different unique correlation lengths (λ); the produced contaminant concentration distribution represents a unique λ. Finally, the concentration distributions are used to calculate the expected concentration with 95% confidence level which produces contaminant concentration with 95% confidence as a function of correlation lengths (C_λ).

Module 2: Characterization of additional data impacts

The purpose of this second module is to predict the distribution of health risk exposure due to the breakthrough concentration predicted at the receptor for each uncertainty level in subsurface heterogeneity. Health risk assessment is the process that estimates the individuals' exposure to health risk due to the use of contaminated drinking and urban water. The health risk assessment follows the approach of Zhao and Kaluarachchi (2002) where cumulative carcinogenic health risk due to three off-site exposures pathway is calculated using exposure parameters linked to different age groups. The three exposure pathways considered here are ingestion, inhalation, and dermal exposure. Typically, individuals' health risk is a function of the dose and individual characteristics. Therefore, heterogeneity in individuals' characteristics produces different health risk exposures for one contaminant level (Bogen, Conrado, and Robison, 1997).

In this study, health risk assessment integrates uncertainty in subsurface heterogeneity and inter-individual variability in health risk exposure parameters. The total health risk (TR) for individual i is defined as the total off-site exposure to health risk as follows

$$TR_i = f(C_\lambda, X_i) = R_g + R_h + R_d \tag{2}$$

where C_λ is the contaminant concentration at 95% confidence estimated at λ, R_g is health risk exposure due to ingestion, R_h is health risk exposure due to inhalation, and R_d is health risk exposure due to dermal contact of contaminated water source, X_i is a vector of age-dependent exposure parameters such as body weight, and skin surface area.

The analysis of health risk exposure using Equation 2 recognizes the inter-individuals' heterogeneity by integrating X_i which is generated in the variability loop as shown in Figure 2. Inter-individual variability is represented by sampling recommended probabilistic distributions instead of fixed values for population exposure parameters such as water intake rate and skin surface area (US EPA, 1997). In this work, appropriate age-dependent probabilistic distributions of exposure parameters are employed in a Monte Carlo sampling process to simulate the population characteristics (US Census Bureau, 2006). Once these parameters are known, carcinogenic health risk can be computed (using Equation 2) as per guidelines suggested by US EPA (Maxwell et al., 1998; Zhao and Kaluarachchi, 2002). Also, Equation 2 integrates uncertainty in subsurface heterogeneity by using expected contaminant concentration calculated in module 2 (C_λ) as an input to the three exposure quantities (R_g, R_h, and R_d). In this work, expected concentration is an exogenous input since it is explicitly determined by the different K spatial structures and lengths.

A joint uncertainty and variability (JUV) analysis compute the exposure to health risk response in two dimensions. First, the uncertainty due to subsurface heterogeneity represented by the spatial distribution of K, second, the variability due to age-dependent population characteristics. Similar to Daniels, Bogen, and Hall (2000) and Maxwell et al. (1998), the JUV analysis is performed through a nested Monte Carlo method where the inner loop represents uncertainty and the outer loop represents variability. The output of JUV analysis is a three-dimensional risk surface with one axis representing uncertainty due subsurface heterogeneity and the other representing variability in population exposure parameters.

Module 3: Welfare and Socioeconomic Analysis

The groundwater monitoring literature indicates that uncertainty in subsurface heterogeneity has established health risk impacts (for example, Maxwell et al., 1998; Maxwell and Kastenberg, 1999); however, there is lack of research addressing the welfare impacts of the produced expected health risks. To the best of our knowledge, no prior study has attempted to quantify the social welfare benefit (in monetary terms) for decisions of improved data collection on subsurface heterogeneity using benefit transfer approach. Therefore, the third module described in Figure 3 represents an original contribution to risk assessment under uncertainty.

The output of the welfare analysis is estimates of individuals' WTP to reduce uncertainty in subsurface heterogeneity by collecting additional spatial information to estimate exposure to health risk with higher accuracy. The theory relevant to social welfare analysis using the BTM is properly presented in other works such as Smith, Van Houtven, and Pattanayak (2006), Florax, Travisi, and NijKamp (2005), and others. Therefore, this paper discussion is limited to the considerations needed to implement the BTM to groundwater monitoring.

Overview of related economic concepts. This work considers the welfare and WTP of the members of a working population exposed to health (mortality) risk due to contamination of drinking water. The population actual exposure to health risk is unknown due to various uncertain system variables such as subsurface heterogeneity.

In this work, actual exposure is viewed as a combination of identified and hidden health risks. We consider that suitable mitigation policies are devised to alleviate the identified risks only and the population remains exposed to the hidden risks.

Health is viewed as a human capital and individuals tend to invest assets to reduce health risk or to achieve more accurate estimation of actual exposure level (Grossman, 1972).

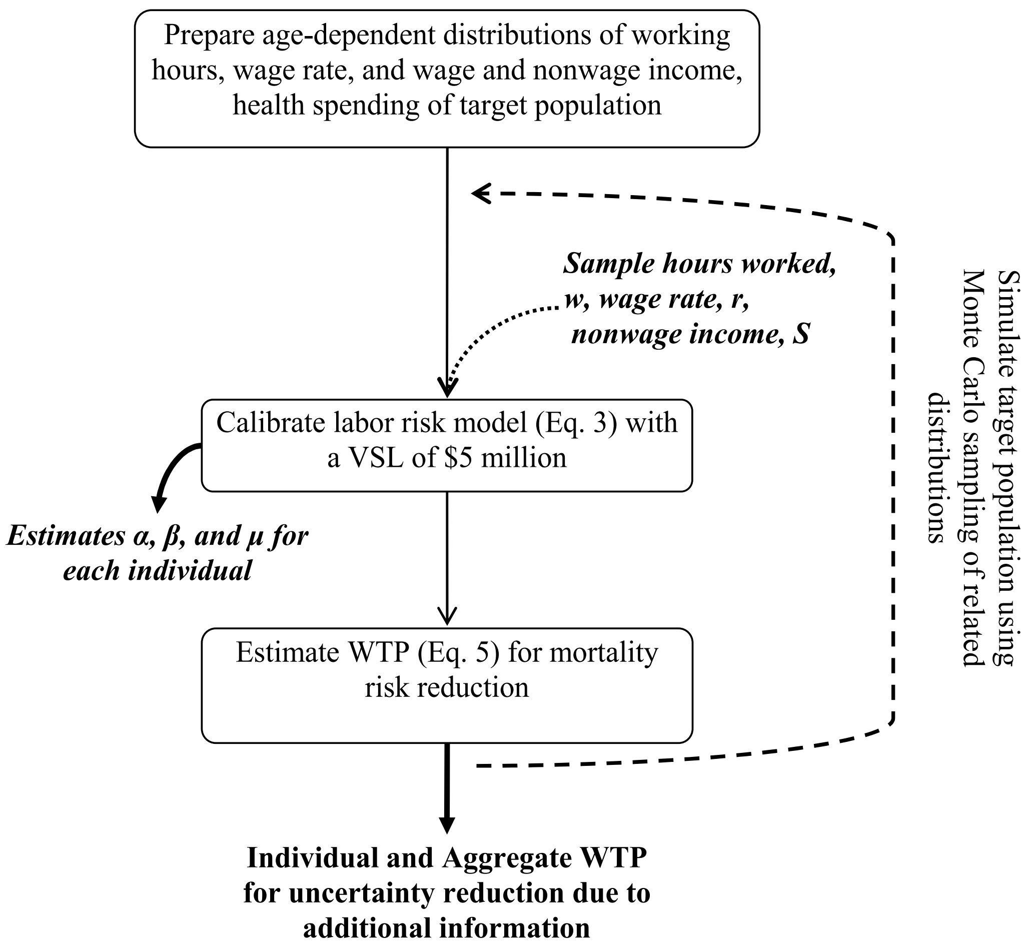

Figure 3. A flow chart describing the welfare and socioeconomic module of the methodology described in Figure 2.

In this analysis an individual with a given income is assumed to allocate expenditure on two pools, 1) on non-health or leisure consumption and 2) health related expenditures with higher priority given to health care. As the exposure to hidden health risk decreases with better information collection, new resources will be released from the health expenditure pool to the leisure consumption pool which produces more utility and higher overall welfare to the individual. Therefore, an additional data collection decision is deemed feasible if it reduces the hidden health risk and identifies higher risk as a result. This concept implies that individuals are risk averse which is a common behavioral assumption in risk assessment (Nadiminti, Mukhopadhyay, and Kriebel, 1996) and indicates that individuals' enjoy higher welfare as risk is identified with higher accuracy and as a result more hidden risk is reduced (Sulganik and Zilcha, 1997).

This analysis defines the household as the economic unit and household members as dependents and heads. In this work, individual is viewed as household head and acts to reduce the expected exposure to health risks among household members. The choice of household level as the economic unit is attractive because it utilizes significant social and economic data (such as consumption, income, etc.) collected over the years at the household level by several agencies.

The standard economic theory suggests that WTP to reduce the expected exposure to health risk is positively related to the magnitude of exposure reduction (Cameron and De Shazo, 2004). Hall and Jones (2007) established that changes in health (mortality) risk (m) from the individuals' perspective can be represented as a change in individual welfare.

Willingness-to-pay analysis. The welfare impact of additional data is determined by simulating a range of decisions designed to reflect increasing levels of information (module 1) which produce matching sets of expected mortality risk (module 2). The change in exposure to mortality risk along with basic population attributes are used to estimate the WTP of target population. In general, WTP is the monetary equivalent of the welfare impact of change in expected exposure to health risk such as mortality (Krupnick et al., 2002).

This work uses the benefit transfer method to derive the economic values of potential decisions. There are several types of benefit transfer methods with varying sophistication levels which are described in the work of Smith, Van Houtven, and Pattanayak (2002, 2006). This analysis uses the Structural Benefit Transfer (SBT) approach which imposes a theoretical behavioral model on existing welfare estimate for a similar empirical study to calibrate the behavioral model and estimates its parameters for a new case study.

In environmental risk literature, SBT models are often constructed in the context of labor markets using labor/risk models based on the compensation workers are willing to accept to assume increased risks of job related mortality. Recently, labor/risk models were introduced to air and water quality improvement problems of (Smith, Van Houtven, and Pattanayak, 2003).

Models describing the labor/risk tradeoff focus on a decision process that envisions individuals selecting among an array of jobs with different risk levels and accordingly different compensations (Smith, Van Houtven, and Pattanayak, 2006). Likewise, we consider that individuals can select among an array of MN designs for contaminated groundwater aquifer with different spatial data collection and different expected risk levels. Therefore, individuals are willing to accept compensation to assume increased hidden health risks of uncertainty in contaminated groundwater assessment. Given a range of MN designs at different spatial data collection levels with varying identified and hidden risks, individuals will seek to maximize expected utility in their decision making.

Pattanayak, Smith, and Van Houtven (2004) proposed a semi-log labor supply model and derived formulations to assess the following three endpoints: expected utility, VSL, and WTP. For an individual i with w annual labor supply (hours worked/year), r hourly wage rate (\$/hr), and S annual non-wage income (\$/yr), the labor supply model is defined for individual i as follows

$$\ln(w_i) = \alpha_i + \beta_i r_i + \mu_i S_i \tag{3}$$

where α_i, β_i, and μ_i are empirical parameters describing the behavior of individual i.

The assumptions of the original model described in Equation 3 are valid for the assessment of mortality risk due to contaminated groundwater. Pattanayak, Smith, and Van Houtven (2004) assume that individuals choose income represented as labor hours supplied and wage rate of a selected job with higher risk. In contaminated groundwater monitoring, we envision individuals will select income similarly but for a risk determined by a selected MN design.

Pattanayak, Smith, and Van Houtven (2004) estimated WTP based on probability of death (mortality risk) related to the job type as shown in Equation 4. Due to space constraints we refer the interested reader to the original paper of the authors for a detailed discussion of this model development.

$$W\tilde{T}P_i = \frac{1}{\mu_i} \ln\left[1 + \frac{\mu_i}{\beta_i}.(p_0 - p_1).\exp(\alpha_i + \beta_i r_i + \mu_i S_i)\right] \tag{4}$$

where p_0 and p_1 are the probabilities of death on the job at the baseline and with a new policy.

In this work, the expected mortality risk due to a selected MN design (m) is identical to the job related mortality risk (p) in the original work of Pattanayak, Smith and Van Houtven (2004). Therefore, utilizing m instead of p in Equation 4 produces WTP estimates to reduce risk of uncertainty in contaminated groundwater monitoring and seamlessly connects the work of modules 1 and 2 to the welfare analysis in module 3. The WTP formulation appropriate for contaminated groundwater monitoring is:

$$W\tilde{T}P_{i(0,1)} = \frac{1}{\mu_i} \ln\left[1 + \frac{\mu_i}{b_i}(m_0 - m_1)\exp(a_i + b_i r_i + \mu_i S_i)\right] \tag{5}$$

where m_0 and m_1 are expected mortality risk due to contaminated groundwater at two MN designs with different spatial data collection levels.

Technically, Equation 5 estimates the compensating variation between two mortality risk levels determined by different spatial data collection levels. Therefore, the compensating variation estimate which is defined as the amount of income that makes an individual indifferent between two different risk levels can be defined in terms of data collection. The WTP estimated in Equation 5 is envisioned as the compensating variation between two data collection levels. Thus, estimated compensating variation represents WTP to collect additional spatial data.

Stochastic simulation of WTP model. In this analysis, there exist several stochastic elements in the uncertainty and variability assessment. Similar to the health risk exposure estimation in module 2; the labor/risk model summarized in Equations 3 and 5 is estimated for individual i of the population using Monte Carlo sampling of probabilistic distributions for related population variables. The nested Monte Carlo approach provides the computational capacity to separate the uncertainty and variability properly and it is utilized in similar groundwater/risk studies (Maxwell et al., 1998; Maxwell and Kastenberg, 1999). The nested Monte Carlo approach (depicted in Figure 2) is composed of two loops: 1) an outer structured uncertainty loop and 2) inner variability loop. The outer loop is based on subsurface heterogeneity. A range of subsurface heterogeneity levels is assumed and the matching field correlation lengths (λ) are used to generate the ensembles of equally likely realizations of K fields. The inner loop purpose is to analyze resulting expected exposure to health risk using the procedure described in (Maxwell and Kastenberg, 1999). Each K field realization provides the breakthrough concentration at the receptor from which the maximum of the 30-year average is computed. The maximum of 30-year average for one correlation length is used to construct probabilistic distributions of concentrations from which the 95th probability (C_λ) is used to estimate the mortality risk. The mortality risk values are used as inputs to the WTP equation.

Management Application

Description of case study

To show the contribution of this work; we will expand on the numerical example of Maxwell and Kastenberg (1999). In this example, a point source of carcinogen is discharging at an upstream location from a municipal water supply well affecting a down-gradient community. Similar to Maxwell and Kastenberg (1999), a two-dimension regional aquifer composed of unconfined sandy fluvial material with 4 km in length and 2 km in width, and 100 m thick was used in the analysis. A population is assumed to be located down-gradient of the municipal well that provides drinking to the community as shown in Figure 4. A constant leaking source of trichloroethylene (TCE) is introduced 3 km upstream of the well at an estimated concentration of 100 ppm for ten years. TCE is a common carcinogen used as an industrial solvent and found at many hazardous waste sites. TCE has a low maximum contaminant level of 5 ppb established by the US EPA.

For demonstration purposes, a target population of 5,000 individuals in the community is affected by contaminated groundwater. The simulated population characteristics are for the random population of the State of Utah for the year 2000. The data include probabilistic distributions of 1) health risk exposure parameters such age and body weight, 2) labor/risk model variables such as wage rate and working hours, and 3) related population properties namely the health state.

Results and discussion

Additional data scenarios simulation. A set of realizations of K fields are produced based on variable spatial K correlation lengths (λ). The spatial variability of K is a major factor in the design of a groundwater MN. In this example, we consider an aquifer with unknown subsurface heterogeneity with an area of 6 km^2 (or 3 km x 2 km).

If the present information indicates a field with a correlation scale of 112 m, then 120 monitoring wells are needed. Likewise, if the present information indicates a more heterogeneous field with a correlation scale of 22 m, the number increases to 3,000 monitoring wells. Therefore, reducing uncertainty in subsurface heterogeneity is economically expensive.

For each K correlation length (λ), an ensemble of 500 equally likely random realizations of K fields is generated using a mean K of 10 m/day and a variance of ln K of 1. In this work, the correlation length (λ) is changed from 2 m for the most heterogeneous case to 502 m to represent a fairly homogenous medium.

We follow the recommendations of Tompson and Gelhar (1990) in selecting spatial discretization to simulate flow and transport. The K fields are generated using the Turning Bands method (Tompson, Ababou, and Gelhar, 1989) before they are used in the groundwater flow model MODFLOW (Harbaugh and McDonald, 1996) to simulate the flow field. Then, fate and transport of TCE is simulated using the MT3D model (Zheng and Wang, 1999).

The flow domain consists of a single layer of aquifer with flow occurring in areal two-dimensional flow field. Fate and transport consists of advective-dispersive mass transport with linear sorption and first-order decay.

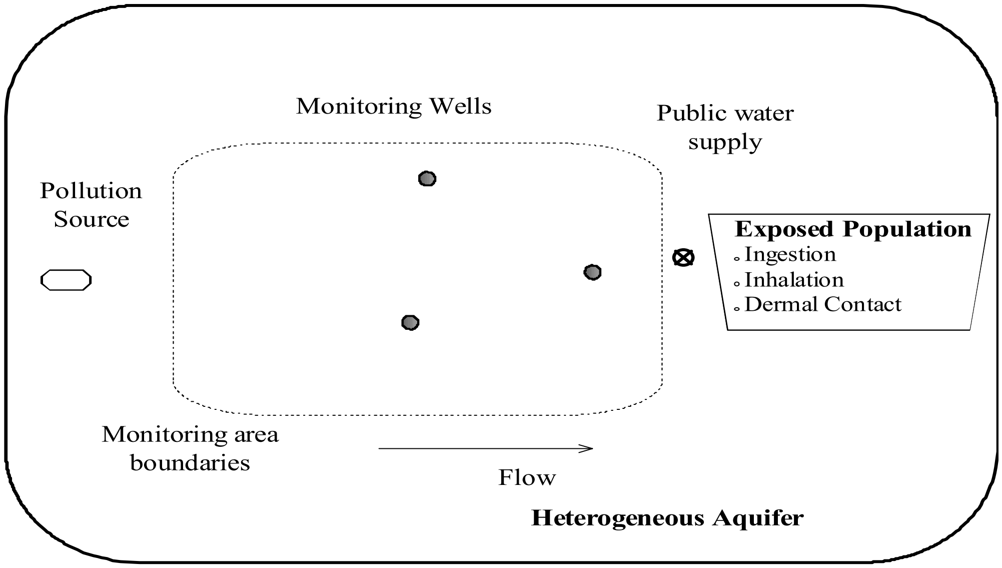

Figure 4. The areal layout of the aquifer used in the numerical experiment. The length and width of the aquifer are 3 and 2 km, respectively. The public water supply well is located 3 km downstream of the pollution source. The monitoring area with monitoring wells denoted here is for representation purposes only.

The values of flow and transport properties used include longitudinal and transverse dispersivity values of 5 and 0.5 m, respectively, and the well discharge was assumed to be 1,000 m^3/day. These values are similar to the values used by Maxwell et al. (1998) and Maxwell and Kastenberg (1999).

Health risk assessment. For each breakthrough concentration profile produced for specific uncertainty level of subsurface heterogeneity (K correlation length); the TCE concentration at 95 % probability is computed and used to estimate the population cumulative health risk using the guidelines of US EPA (2001) and the modifications suggested by Zhao and Kaluarachchi (2002).

The exposure-related population characteristics are presented as age-dependent probabilistic distributions following Zhao and Kaluarachchi (2002). Then, probabilistic distribution of age classes for Utah population and the corresponding characteristics are estimated using surveys and empirical studies conducted by various state and federal agencies. In this work, the published data from the Utah Department of Health (UDOH, 2006) were used.

Using Monte Carlo sampling approach; the representative population of the state of Utah is simulated. For the exposure parameters, age-dependent distributions of ingestion, inhalation, and dermal exposure parameters (except slope factors) were developed from published data (Table 1).

The results of the JUV analysis for uncertainty in subsurface heterogeneity and variability in exposure parameters due to age-dependent population characteristics are shown next. The results of this analysis show that the receptor concentration increases as the subsurface becomes more heterogeneous (or small λ values) compared to a less heterogeneous case (or higher λ values) and this observation is similar to the results of Maxwell et al. (1998). Figure 5 indicates that at a confidence level of 95%; a heterogeneous subsurface structure (or smaller λ) produces a higher contaminant concentration.

The three-dimensional view of the risk profile obtained from the JUV analysis is shown in Figure 6 . The health risk surface indicates a robust impact of the variability of population parameters which attempts to conceal the impact of uncertainty due to subsurface heterogeneity.

Table 1. A summary of the sources and types of data used in the individual exposure to health risk

Variable	Typical Values	Unit	Value used in this Study
Age	Variable	yrs	US Census Bureau International Data Base, 2006 using data from year 2006
Body weight	Variable	kg	Age dependent distributions recommended in USEPA 1997[a]
Exposure duration	30	yr	Constant
Exposure frequency	350	day/yr	Constant
Ingestion			
Ingestion rate	Variable	L/day	Uniform distribution with a range of 1.4 to 2.3 L/day; USEPA, 1997[a]
Ingestion slope factor	0.011	1/[mg/Kg-day]	Constant
Inhalation			
Inhalation rate	Variable	m^3/day	Fitted distribution to data using age as the variable; USEPA, 1997[a]
Inhalation slope factor	0.011	1/[mg/Kg-day]	Constant
Dermal Contact			
Dermal contact slope factor	2.67	1/[mg/Kg-day]	Constant
Exposed skin surface area	Variable	cm^2	Function of age and body weight using surface area/body weight ratio; USEPA, 1997[a]
Shower duration	Variable	hr/day	Fitted to distribution in the range of 0.016 to 2 hr/day; USEPA, 1997[a]

[*]EHF is the US EPA Exposure Factors Handbook (1997).

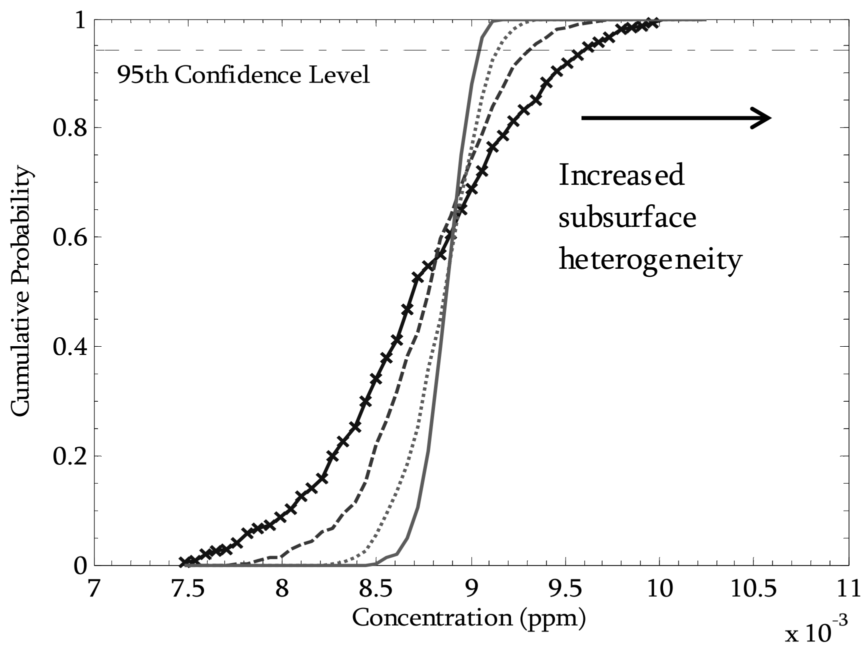

Figure 5. A plot of the cumulative distribution function of maximum 30-year average TCE concentration at the receptor for different correlation scales (502, 302, 112, and 12 meters). A larger correlation scale reflects a more homogeneous structure compared to a small value of correlation scale.

The strong impact of variability of population on health risk is anticipated due to the use of the full range of variability of age-specific individual exposure parameters. Most studies used a single probabilistic distribution to describe a given population characteristic irrespective of the individual age. This approach has significant limitations because exposure and vulnerability of an individual depends largely on age and to some extent on gender. Zhao and Kaluarachchi (2002) showed that age does impact risk predictions while gender plays a minor role across all age groups. These observations are clearly displayed in Figure 6 for any given uncertainty value.

Socioeconomic analysis. The WTP assessment employs labor/risk model that requires calibration using various population data to calibrate Equation 3 and produce individual-specific constants to be used in the benefit transfer formulation.

The needed data for the labor/risk model are obtained from the original work of Pattanayak, Smith, and Van Houtven (2004) and other sources as shown in Table 2.

The calculation approach represents variability among individuals and sets the calibration process at the individual level. To produce individual specific WTP estimates, the parameters of Equation 3 are allowed to evolve freely for each individual (i) using the vector of inputs sampled by the Monte Carlo method (X_i).

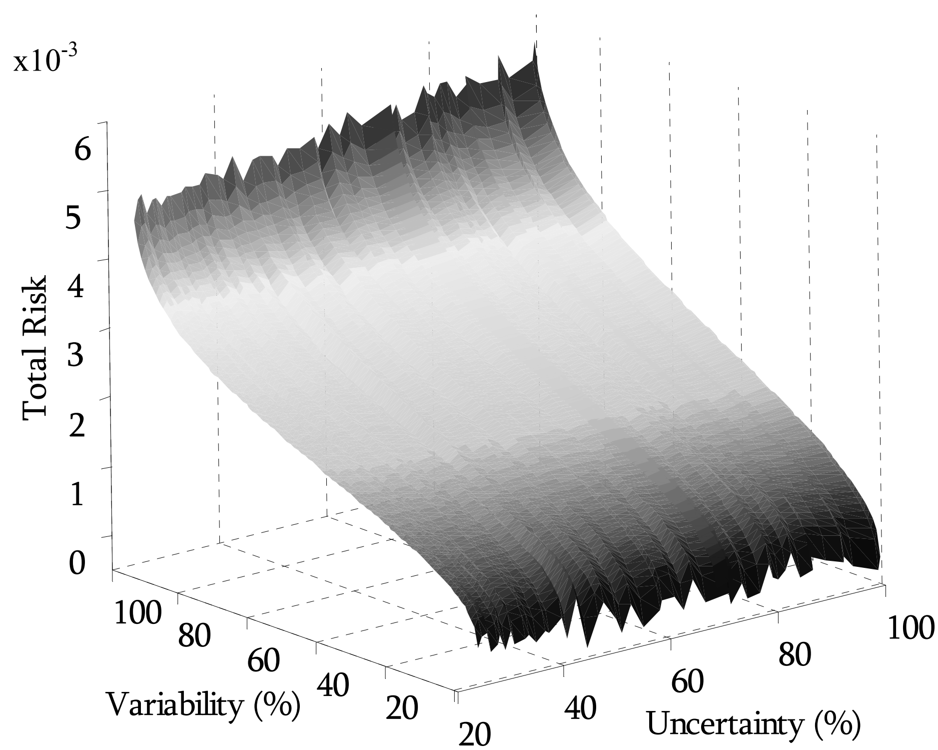

Figure 6. A 3D plot of health risk surface as a function of uncertainty percentile due to subsurface heterogeneity and variability percentile due to population characteristics for a correlation scale of 252 m.

The sampled inputs are individuals' i labor supply, (w_i) wage rates, (r_i) and non-wage income, (S_i). Once the calibrated parameters for an individual i are obtained, the individual WTP for data collection improvement is computed using Equation 5.

An elaborate description of the calibration process is provided in Pattanayak, Smith and Van Houtven (2004) and Smith, Van Houtven, and Pattanayak (2006). A benchmark VSL of $5 million is selected to calibrate the parameter (β_i) in Equation 5 as shown in Smith, Van Houtven, and Pattanayak (2006). A description of the sampled values for Utah population is provided in Table 3.

<u>Calculation example</u>. The purpose of this application is to address the question of estimating how much a specific working population is willing to invest to reduce system uncertainty by obtaining additional information. Given the high uncertainty of subsurface heterogeneity and K correlation length, stakeholders are challenged by the question of how many spatial data points (monitoring wells) should be present in the optimal MN design.

The actual number of wells to be designed is a tradeoff between the cost of construction and monitoring, welfare impact of additional information of subsurface heterogeneity allowing better prediction of health risks to the population, and the WTP of individuals based on their income, health state, and age.

To illustrate the methodology application in groundwater monitoring; consider a representative population of Utah composed of 5000 individuals located downstream of a groundwater contamination source. The base case of K spatial sampling design is based on uncertain K correlation length of 502 m which indicates a fairly homogeneous K spatial structure with minimal data collection requirement.

Table 2. An overview of data sources used in the welfare and socioeconomic analysis

Variable	Type	Level	Description
Related variables			
Mortality risk, m	Fixed values		Calculated in modules 1 and 2 at fixed levels of subsurface heterogeneity (based on K correlation length)
Health state, x_a	Probabilistic distributions	State level	Prepared age-dependent distribution from stated preference survey of general health status using several health indicators (diabetes, asthma, arthritis) for Utah population for 2006[1]
Income, y_i		State level	Age-dependent, US Census Bureau (2000) in 2006 dollars
Labor/Risk model calibration			
Benchmark VSL	Fixed value of $5 million	US National level	Used to calibrate parameter β_i in transfer function (Equation 3)
Labor supply (hours) worked/yr), w_i	Probabilistic distributions	US National level	Age dependent distribution of hours worked.[2]
Wage rate, r_i ($/hr)		State level	Prepared probabilistic distributions of population by occupancy types and matching average wage rates (2006 dollars)[3]
Non-wage income, S_i ($/yr)		State level	Fraction of individual income spent on health care (IBIS-PH, 2007) for Utah population

1- Data as of October, 2006 from Utah Department of Health, Center for Health Data, Indicator-Based Information System for Public Health Web site: http://ibis.health.utah.gov.

2- Source: BLS, 2007. American time use survey-2006 Results, Bureau of Labor Statistics, USDL 07-0930, June. http://www.bls.gov/news.release/archives/atus_06282007.pdf.

3- Source: BLS, 2007. May 2006 State Occupational Employment and Wage Estimates-Utah, May, http://stats.bls.gov/oes/current/oes_ut.htm#(1).

Table 3. Summary statistics for variables used in the simulation of Utah population using Equation 3 and 5

Variable	N	Mean	Standard Deviation	Minimum	Maximum
Daily Hours Worked, w_i	5000	7.80	0.64	4.20	10.50
Hourly Wages ($), r_i	5000	14.63	12.38	2.30	164.58
Non-Wage Income, S_i	5000	13562	3945	2320	46150

To assist in the decision-making process, several potential scenarios of incremental increase of monitoring wells (at reducing correlation lengths, λ) to improve the base case of insufficient sampling (at λ = 502 m) are simulated. For each scenario; the corresponding ensemble of K fields, TCE concentration, and health risk profile are estimated. Then, the labor /risk model is calibrated for Utah population. The empirical parameters of Equation 3 (α_i, β_i, and μ_i) used to calibrate the labor-risk model are estimated for each member before the individual WTP is estimated using Equation 5 to obtain the distribution of WTP of target population. The average estimates of parameters α_i, β_i, and μ_i for Utah population are 92.56, 2.92x 10^{-4}, and -3.24 x 10^{-2} respectively.

For each simulated scenario, the distribution of WTP of the target population was estimated. Figure 7 shows the WTP ($/year) with the simulated scenarios arranged in increasing order from low density (at λ =502 m) to high density (at λ =2 m) spatial sampling designs and with the variability due to age-dependent population characteristics.

The trend of WTP reflects an anticipated social behavior of valuing risk higher when individuals are more vulnerable (with high variability). Also, at a smaller correlation length (or a large number of samples), the WTP increases slightly especially when individuals are at high risk (or high variability). For instance, at 95% confidence level, household members with high vulnerability (at 80% variability) show a WTP starting at \$274/yr for a minimum sampling level (at λ = 502 m) and increasing to \$386/yr for maximum sampling level (at λ = 2 m). This observed trends in Figure 7 are illustrated better in Figure 8 which shows the variation of 95th percentile value of individual WTP (\$/year) with correlation length for different variability values.

Figure 8 shows clearly that the WTP responds to increases in variability in a stronger and a more explicit manner than to increases in the information levels. This observation is explained as follows; variability conveys vulnerability, so as variability increases, individuals' vulnerability increases which explain the elevated WTP for any risk reduction.

Figure 9 shows the variation of 95th percentile annual household WTP with K correlation length. Here the 95th percentile value which can be considered as the most likely value is obtained from Figure 7 corresponding to the 95th percentile uncertainty and variation values. The results of Figure 9 show that for each incremental addition of data; the households' most likely WTP increases slightly as the uncertainty level is reduced.

To emphasize the methodology robustness; we provide a detailed account of the calculation of selected scenarios from the management application described above. As indicated earlier, λ is an indicator of the presumed K spatial correlation structure and the optimal MN design.

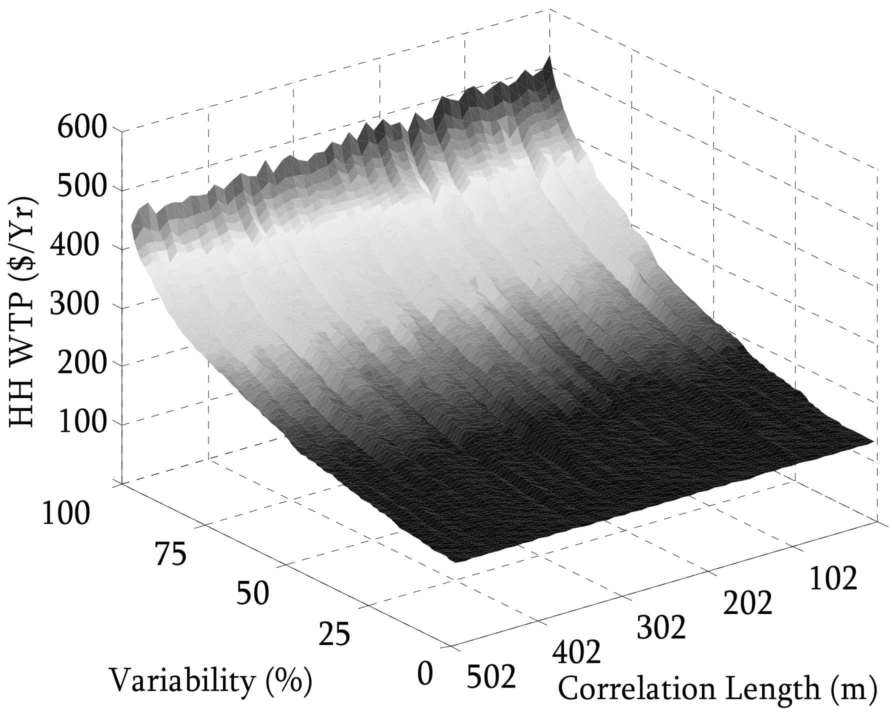

Figure 7. A 3D plot of annual household head WTP at 95th confidence level for all correlation scales and variability of the target population.

Therefore, in the next discussion we use scenarios of λ to contrast the different MN designs and the corresponding data collection levels.

The considered scenarios are as follows, one with λ=112 m and the other with λ=22 m. The data and results provided in Table 4 provide useful management relevant information that can lead to more realistic estimates of population preferences in collecting additional information to reduce hidden risks.

Table 4 shows the results of these two scenarios for various design parameters. The addition of information determined by improving λ from the base case (λ=502 m) to 112 m and to 22 m corresponds to moderate and to high heterogeneous subsurface structures, respectively.

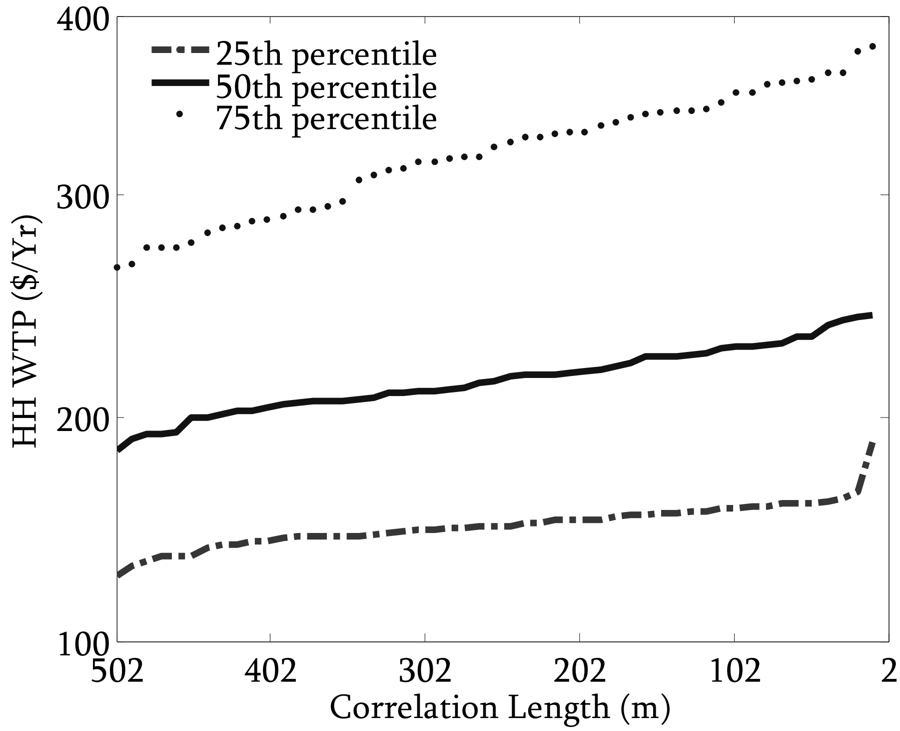

Figure 8. A plot of showing the variation of annual household head WTP at 95th percentile uncertainty and variability with correlation length.

It is seen that the estimated contaminant concentration is higher as the number of samples is increased and becomes more accurate (also known as "Blackwells' effect"). The increase in identified concentration with more data collection indicates that actual concentration is higher than estimated concentration.

In Table 4, the small rise in health risk is related to the use of a wide range of age-dependent population characteristics than using typical fixed values or probabilistic distributions independent of age. However, the small change in health risk is adequate to induce a welfare change at individual and population levels.

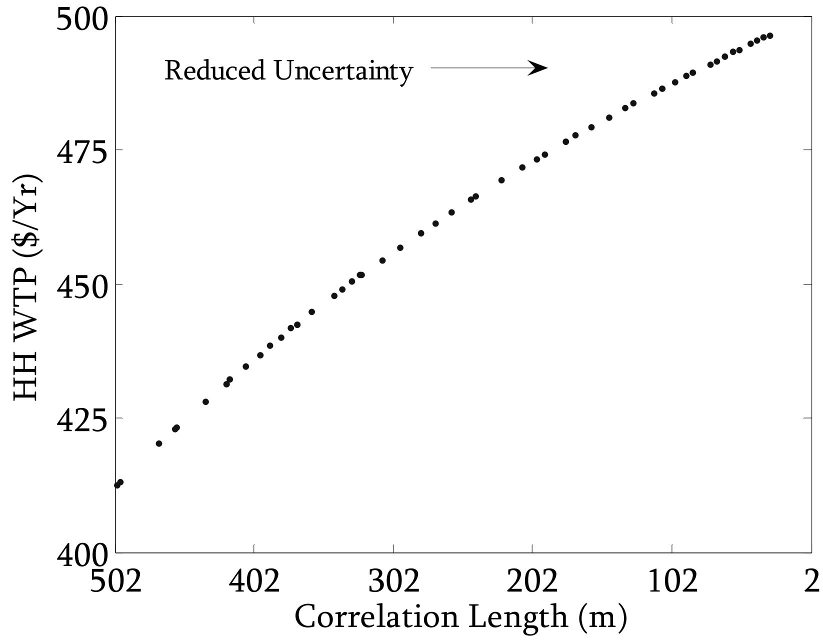

Figure 9. Variation of household head WTP at 95th percentiles of uncertainty and variability with correlation length.

The reduction in uncertainty increases individual utility under the assumption that individuals adjust their risk averting behavior to be proportional to the identified risk level (Abdalla, Roach, and Epp, 1992). Thus, the hidden risk levels due to lack of accurate information become a threat to population health and productivity.

Therefore, an identified higher risk level with additional information produces higher welfare by revealing unknown risk to the population. Using a vector of properties such as age and income; individuals determine their WTP to acquire the additional information and adjust their risk behavior accordingly.

Table 4 shows a higher individual WTP estimate for λ of 22 m than for λ of 112 m by $11/year-individual or by nearly 5%.

Table 4. Data and results of the management example corresponding to two additional data scenarios with correlation scales of 22 and 112 m

Variable	Scenario 1	Scenario 2	Comments
Additional Data Realization			
Information Level	λ =112 m	λ =22 m	2,979 additional locations needed finer resolution monitoring network to better represent subsurface heterogeneity
Number of monitoring locations	120	3,099	
Characterization of Additional Data Impacts			
95th percentile concentration at the receptor	11.8 ppb	20.3 ppb	High resolution monitoring network produces a higher concentration and therefore higher health risk
Change in individual carcinogenic health risk from base case (λ = 502 m)	$2.9\text{x}10^{-4}$	$3.1\text{x}10^{-4}$	
Socioeconomic Estimates			
Calibrated Parameters Statistics			
Benchmark VSL	$5 million (US EPA, 2004)		
Mean	α=92.56, β=2.92x10-4, μ=-3.24x10-2		
Standard deviation	α=12.45, β=7.03x10-5, μ=-0.0076		
Household Heads' WTP ($/yr)			
Median	238	249	A higher risk detected produces higher WTP statistics for additional data.
25th percentile	156	188	
75th percentile	360	386	
SID*	102	99	
Σ Household Heads' WTP for a 5,000 population size			
Total	$\$1.21\text{x}10^{6}$	$\$1.26\text{x}10^{6}$	An increase in population WTP of $55,000

*SID is the Semi Interquartile Deviation. SID= (75th percentile -25th percentile)/2=inter quartile range/2 and accounts for 50% of the data (median and 1 standard deviation around the median).

We observe a similar range in the WTP values for the two improvement levels which is supported by the close values of the spread measure statistic (i.e., SID) for the 112 and the 22 m correlation structure.

Also, Table 4 provides estimates for improving groundwater monitoring by additional data collection. From a decision-maker's point of view, the aggregate WTP for a proposed improvement in MN design from λ of 502 m to λ of 112 m represents an increase in population welfare by \$1.21x10^6 per year. Likewise, a proposed improvement in MN design from λ of 502 m to λ of 22 m increases population welfare by \$1.26x10^6 per year. Therefore, by comparison one can indirectly estimate the increase in population welfare due to reducing uncertainty in subsurface heterogeneity (from a MN design of λ = 112 m to λ = 22 m) by \$55,000 per year for a population of 5000 individuals in Utah or \$11 per person per year for the improvement in data collection.

To summarize, the suggested framework calculations shown in Table 4 enhances the benefit-cost analysis capacity to elicit welfare impacts of decisions using practical approach which is a challenge in socioeconomic problems.

<u>Sensitivity and validity analysis</u>. Differences between individuals exist and may be associated with age, gender, or health state (Dickie and Ulery, 2001). Researchers noted that age determines the individuals' health state and therefore their exposure to risk and welfare (Johannesson, Johansson, and Lofgren, 1997; Krupnick et al., 2002). For instance, Krupnick et al. (2002) investigated the impact of age on individual's valuation of risk in VSL which is a less specific measure than WTP. The authors found no statistical difference in the VSL across ages until age 70 years and above.

The findings of the study of Krupnick et al. (2002) were in agreement with the earlier study by Jones-Lee, Hammerton, and Philips (1985) where the VSL for individuals with age above 70 years is lower than individuals of age 40 years.

We investigate the interaction of WTP with important population parameters such as age, health state, income, and income loss due to illness represented as loss in working hours. The simulated population's income-age relationship (shown in Figure 10) indicates a theoretically sound trend of increasing income until middle age where the majority of population resides. For old age groups which represent a small fraction of the population, we observe a large variation in income.

The general trend between ages 50 and 75 years old indicates a decreasing trend in the three percentiles. This pattern reflects a loss of income due to retirement. For age groups after 75 years, the trend should be analyzed cautiously. The rise of median and 90th percentile for ages older than 75 years is interpreted by the simulation process and data sources. The old age groups (beyond age 75 years) represent a small percentage of this population.

For a less populated age group, therefore, the weight of one data point on the general trend can be significant. Individuals of old age groups have a wide range of incomes; some have a steady low retirement income while others enjoy a higher steady income regardless of age either because they are self-employed or own profitable investments.

In essence, there is an unstable trend for old age groups (beyond 75 years) and due to the small fraction of population that is greater than 75 years, it is not appropriate to use the trends observed in this age group in further analysis.

The income profile was evaluated as a function of health state and shown in Figure 11. Two distinct trends of annual income versus health state are observed. The results are explained by the age correlation with health state (Figure 12) and with income (Figure 10). Region A represents individuals with low health states ranging from 0.1 to 0.5.

Region A is dominated by old age individuals (> 60 years) with poor health as revealed in the empirical results shown in Figure 12. Typically, old age individuals have steady retirement income and the income is less likely to change with time. Region B represents a high health state of 0.5 to 0.9 capturing the majority of the population. In Region B, the median income decreases in a fluctuating pattern as the health state increases.

Figure 10. Variation of individual income ($/yr) as a function of age showing the median, and 10th and 90th confidence intervals for the simulated population based on probabilistic distribution of US Census (2006) for the State of Utah.

The pattern in Region B indicates a wide range of incomes for a given health state. Individual age in Region B is dominated by young ages and the income for young age groups show an increasing trend as shown in Figure 10.

Therefore, the decreasing income trend of Region B is expected because age is inversely related to the health state. This pattern is consistent with the economic theory and anticipated social behavior where income is positively related to the WTP for environmental improvement (Horowitz and McConnell, 2001).

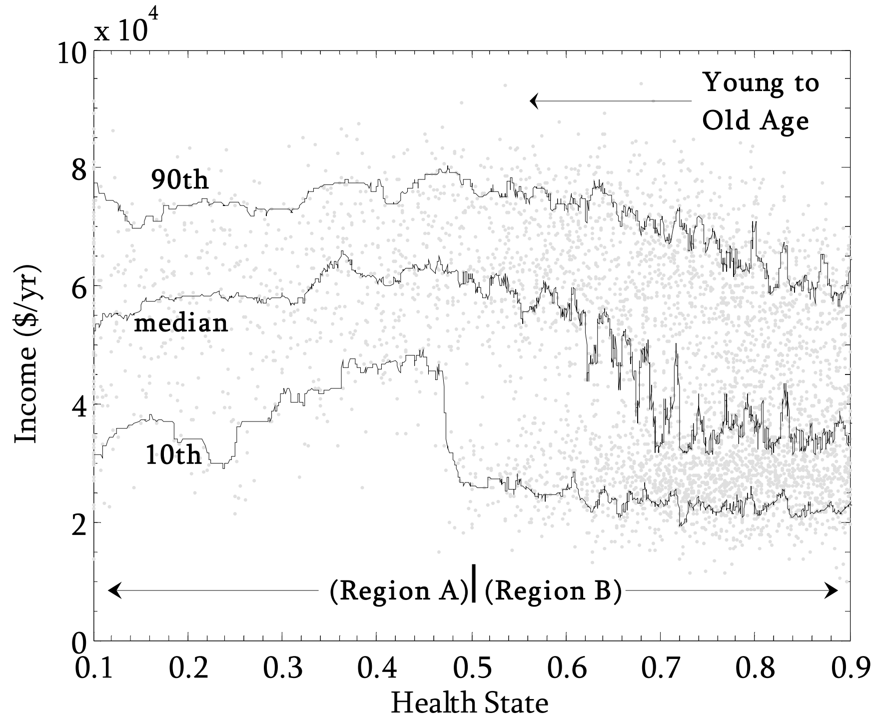

Figure 11. The distribution of individuals' health state with household income of the target population showing the median, and 10th and 90th percent confidence intervals. The distribution uses age-dependent probabilistic distributions of income (Figure 10) and health state (Figure 12) for the population of the State of Utah.

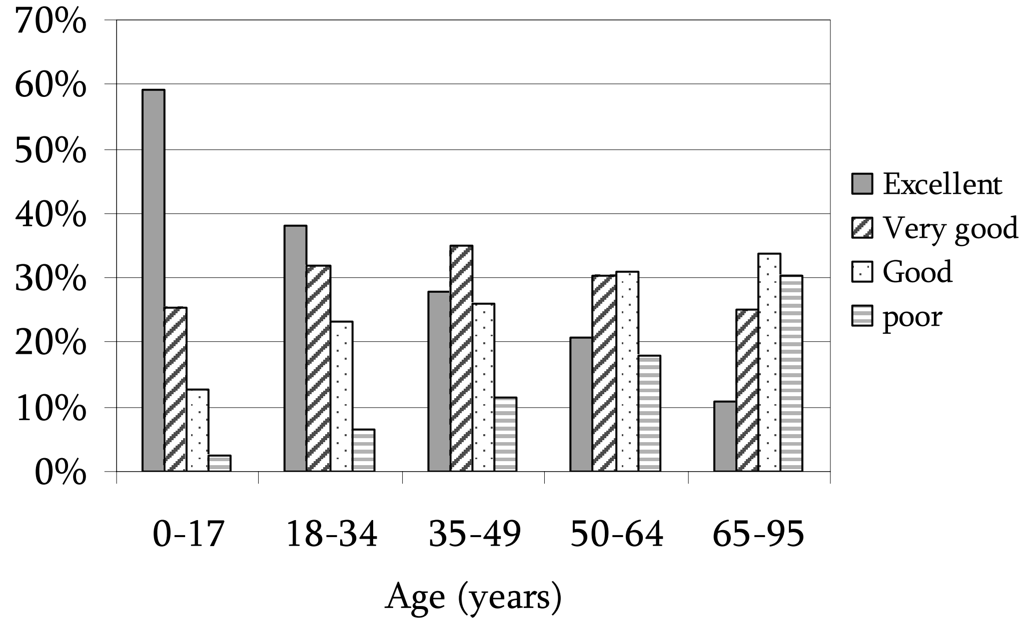

Figure 12. The Individuals' health state profile presented by age groups. Estimates are extracted from health status survey of the population of the State of Utah (UDOH, 2006). Survey included chronic diseases (i.e. diabetes, arthritis, asthma). This distribution is used for evaluation of potential trends with WTP estimates.

In Figure 13, we examine potential trends of related variables on WTP estimation. Age impacts on WTP are robust. At a young age of 20 to 40 years, the low median and high variation shown in Figure 13 (a) is attributed to the large spectrum of income and high health state of individuals in the young age groups.

The increase in WTP at higher income shown in Figure 13 (b) is expected at high health state. The reducing tendency of middle age groups is attributed to reduced health state. In relation to labor/risk analysis, individuals' health state affects individual productivity in terms of working hours.

The age-dependent distribution of annual lost working hours due to illness shown in Figure 13 (c) indicates a similar trend to the estimated health state. The health state trend shown in Figure 13 (d) suggests that individuals with better health states are willing to pay more to avoid risks than individuals with initial health problems.

Summary and Conclusions

The goal of this work is to extend the benefit-cost analysis of contaminated groundwater management by integrating socioeconomic measures of related decisions. In this study, a methodology is proposed to assess welfare benefits of decisions aimed at reducing uncertainty by collecting additional data.

This work developed an interdisciplinary framework that introduces rigorous socioeconomic concepts that are new to the benefit-cost approach used in groundwater contamination monitoring and utilizing the works of Maxwell and Kastenberg (1999) and Pattanayak, Smith, and Van Houtven (2004).

The three modules of the methodology consists of: (1) additional data selection and realization; (2) characterization of additional data impacts, and (3) the welfare and socioeconomic analysis.

The initial two modules adopted the approach of Maxwell et al. (1998) and Maxwell and Kastenberg (1999). Our welfare-economic analysis enhances MN design considering appropriate welfare measures such as WTP for risk reduction.

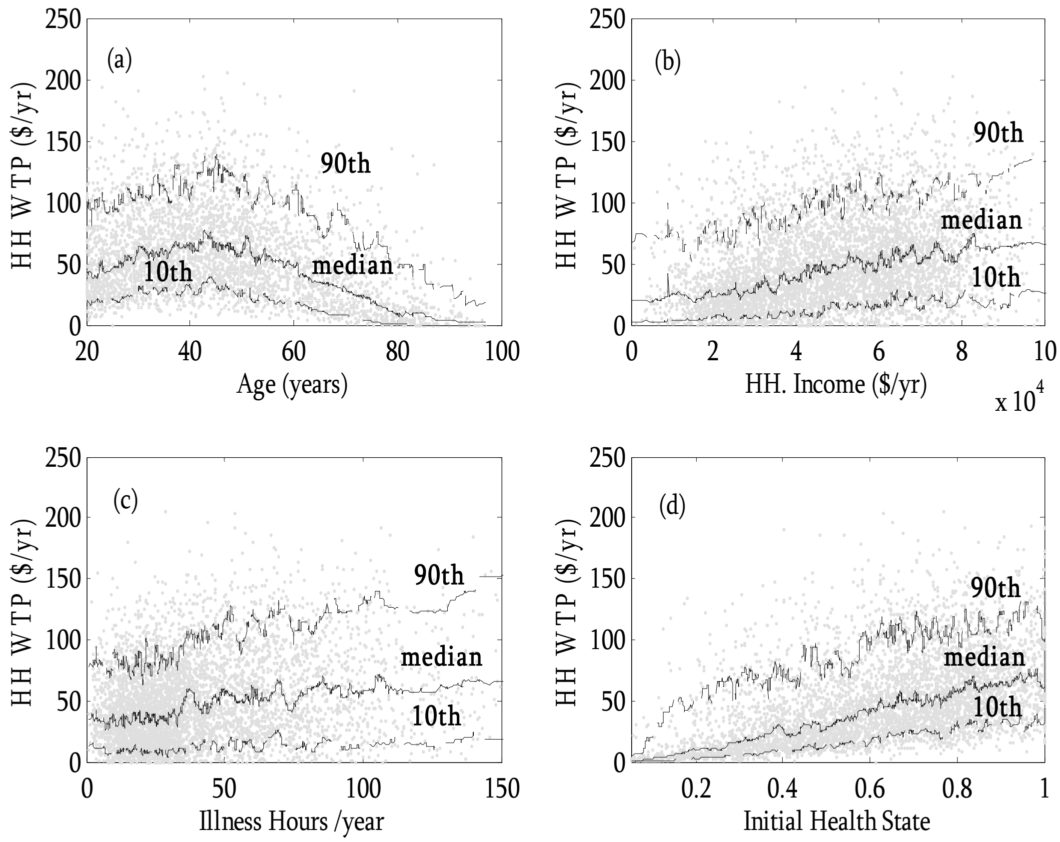

Figure 13. Diagnostic curves of the annual household head WTP ($) as a function of (a) age, (b) annual household income, (c) illness hours per year, and (d) initial health state for 20% reduction in risk due to a proposed data gathering effort. The curves represent median, 10th and 90th percentile confidence intervals.

The methodology evaluated the WTP using the change in expected mortality risk evaluated by a labor/risk model.

The proposed methodology is applied to the theoretical case study adopted in Maxwell and Kastenberg (1999) where health risk impacts of carcinogenic point-source contaminant are evaluated. The age-dependent characteristics of the target population were represented through probabilistic distributions of income, age, and risk exposure parameters.

The proposed methodology produces predictions of WTP that are consistent with the patterns expected in the economic theory and similar benefit transfer studies. The JUV analysis indicates that the variability in population (largely due to age) has higher impact on exposure to health risk and WTP than uncertainty due to subsurface heterogeneity. This pattern arises due to the extended range of variability of individual health exposure parameters selected to achieve accurate characterization of population variability. The expanded range of exposure parameters is recommended in similar health risk studies (Maxwell et al., 1998; Zhao and Kaluarachchi, 2002). The economic analysis assumes that reduction in hidden health risks results in higher welfare. The WTP estimates showed a declining trend for old age groups (>50 years) which indicates that the age-dependent health state has a strong impact on welfare measures.

The proposed methodology is limited to predictions of a single-period which in this case is on annual basis. However, the methodology has the advantage of allowing stakeholder to allocate risk-reduction expenditures based on explicit monetary estimates of gain in welfare due to uncertainty reducing decisions.

The premise of the methodology is to provide an alternative to traditional contingent valuation methods to assess social welfare. The proposed methodology extends beyond putting together disparate estimates of similar cases from different valuation methods; instead, the method utilizes these estimates along with a “theoretically sound” structure to produce transferable and adaptable estimates to different scenarios. The approval of this methodology depends on these factors, (1) the data quality and (2) the lack of robust procedure to assess the validity of the new benefit estimates.

As for data quality, several agencies and studies provide adequate sources in usable format to this work. These data sources are typically available from different state and federal agencies.

As for validity, comparing trends of variables and predictions of new benefit estimates with existing survey-based studies is the recommended practice. The proposed methodology is attractive because it requires data from sources that are generally accessible, for example, public domain socioeconomic databases on age, income, health statistics, etc., thus permitting its application on different environmental problems.

CHAPTER V

SOCIOECONOMIC ANALYSIS TO ASSESS ADDITIONAL DATA COLLECTION STRATEGIES AND CORRESPONDING WILLINGNESS-TO-PAY IN WATER QUALITY MITIGATION

Poorly managed data collection programs and hydrologic variability produce gaps in water quality data which causes significant uncertainty in water quality management.

Decision-makers are inclined to improve data collection programs to reduce uncertainty; however, such improvements are hindered by limited resources and high costs. Therefore, an important question is how to allocate limited resources to collect additional information to better estimate the risks versus the willingness-to-pay (WTP) by the society. This work proposes an interdisciplinary methodology to estimate the social benefits of additional data collection to reduce uncertainty produced by hydrologic variability in water quality mitigation. The methodology utilizes the benefit transfer method that allows the transfer to a new geographic and population setting using readily accessible public-domain data.

The methodology consists of determining the impacts of different information levels, assessment of utility at each information level, and combining utility with age-dependent socioeconomic characteristics of the population to predict the WTP. The applicability of the methodology was demonstrated to Fishtrap Creek Catchment of Washington State due to phosphorus loading affecting water quality and hence recreational activities. The results showed that the proposed methodology has significant potential to determine resources allocation in mitigation activities based on societal WTP for such work.

Introduction

Water quality problems remain a challenge in many regions of the nation (US EPA, 2002). Nutrient rich runoff is the most widespread pollution source; it affects about half of the impaired lake areas and about 60% of the impaired river reaches (Carpenter et al., 1998). The increased loading of nutrients causes eutrophication of water bodies which produces unwanted algal growth, depletion of oxygen levels, degradation of fish habitats, and even increases filtration costs (US EPA, 2003; Poor et al., 2001).

Water quality in the US has improved significantly as a result of successful mitigation of point sources and the use of total maximum daily loads (TMDL) plans to control non point source (NPS) pollution (Ribaudo and Horan, 1999). Nonpoint source pollution is believed to be the major source of polluted runoff loading to water bodies, accounting for approximately 70% of total suspended solids and 80% of total phosphorus (TP) input (Kim, Choi, and Stenstrom, 2003). NPS pollution is difficult to measure and manage (Bennet et al., 1999; Sharpley et al., 2001). NPS pollution management faces practical and public policy challenges. Decision-makers are faced with technical challenges arising from uncertainty in remedial measures, and efficiency and policy challenges arising from uncertainty in determining the contributions of polluters and hydrologic variability.

Significant uncertainty in NPS loadings emanates from variable hydrologic processes such as rainfall, erosion, and runoff (Worrall and Burt, 1999). Hydrologic processes exhibit variability at temporal and spatial scales which have shown as uncertainty in pollution prediction and mitigation. Runoff and erosion processes which determine pollutant loadings are seasonal in nature, therefore, intensive sampling is needed to assess the pollutant loadings accurately.

Characterization of temporal changes in surface water quality is a critical aspect for evaluating NPS pollution (Ouyang et al., 2006). Typically, hydrologic variability is assessed through its impact on nutrient export coefficients (Endreny and Wood, 2003; Khadam and Kaluarachchi, 2006a; Sharpley, McDowell, and Kleinman, 2001 and Sharpley et al., 2002). Export coefficients for nutrients such as nitrogen and phosphorus (P) are established based on estimates of runoff nutrient loads as a function of land use type (Soranno et al., 1996). By definition, export coefficients are sensitive to spatial and temporal changes of hydrologic processes (i.e. runoff) and changes in land use and management practices (Hanrahan et al., 2001). Export coefficients (EC) have been used by the US Environmental Protection Agency (US EPA) in numerous NPS management applications (Soranno et al., 1996). Moreover, all water quality models utilize some form of EC to estimate NPS pollutant loadings. Therefore, EC can be used as a proxy of uncertainty due to hydrologic variability.

Practically, decision-makers observe random signals of nutrient loading to a water body at discrete points in time at a given sampling interval. The discrete data points are used to estimate the annual NPS pollutant loadings which provide the basis for policy evaluation. In the context of data collection; an assumption of constancy is implied where stability in pollutant releases between samplings is assumed to validate the annual loading estimates. This assumption overlooks the impact of hydrologic variability and introduces uncertainty in pollutant loading estimations. This uncertainty imposes negative effects on mitigation efforts. Decision-makers tend to relate observed pollution to land use practices which translates to additional restrictions on the economic productivity of stakeholders due to misidentification of pollution sources. In this sense, the benefit of reducing uncertainty is two-fold: (1) it protects producers from additional economic losses due to imposing of costly overprotective measures and (2) it protects against unexpected shock loads which cause unwanted consequences on related recreational activities such as fishing.

Appropriate economic valuation of water quality entails combining estimates of market and non-market uses of water (Chao, Whittington, and Lauria, 1996). When pollution of water bodies is considered; a non-market value emanates from recreational services such as swimming, fishing, and scenery. These uses of water would be the first to suffer due to pollution events. Therefore, benefits of acquiring better information to reduce uncertainty in NPS loading affects an array of economic activities and social functions (non-market values) which causes a typical benefit-cost analysis to fall short in cases of natural water quality protection (Navrud, 2001). In this work, this deficiency in benefit-cost analysis is addressed and focuses on the assessment of benefits of non-use values through a practical and a transferable methodology.

Economists have devised several valuation methods for natural resources. Valuation methods are classified into revealed preference, where valuations are inferred from actual observations of choice behavior, and stated preference, where the valuations are directly obtained from hypothetical statements of choice (Kolstad, 2004). The revealed preference methods include Hedonic Pricing and Travel Cost Methods. For the stated preference methods, people are presented with a hypothetical scenario and then asked to state explicitly what its worth to them. Economic valuation using direct approach (i.e. contingent valuation method) is the “first-best” strategy to collect the needed information. The stated preference methods are deemed to be more accurate for conducting benefit-cost analysis for environmental resources (Loomis, 1996). However, most stated preference studies are expensive and frequently unfeasible. When stated preference methods are not feasible; then the Benefit Transfer Method (BTM) emerges as a “second-best” option to evaluate management and policy impacts. Even though the reliability of BTM is debatable; it remains attractive compared to the stated preference methods because it does not require expensive and lengthy data collection (Desvousges et al. 1992; Brouwer, 2000). The BTM is increasingly applied in policy evaluations related to recreational use assessment (Bergstrom and De Civita, 1999). The benefit transfer can be conducted by deriving a benefit function that allows adjustment of previous estimates for a new site with different population characteristics (Smith et al., 2000; Loomis, 1996).

In this work, a structural meta analysis is used to apply the BTM. The meta analysis approach utilizes theoretically sound behavioral model (a benefit transfer function) and uses established benefit estimates in the literature for the same commodity such as improving water quality (Pattanayak, Smith, and Van Houtven, 2004).

In this paper, we develop an interdisciplinary socioeconomic framework to assess welfare impacts of decisions relevant to data collection at given sampling intervals to reduce uncertainty in NPS loadings. A major challenge in this analysis is to represent decision impacts in usable terms for welfare analysis. In this work, we propose to develop an indicator parameter that estimates the impacts of uncertainty in NPS loading due to hydrologic variability as a function of data collection level which can be used in welfare analysis. This measure, hereafter referred to as uncertainty indicator, is structured to predict undetected NPS loading as a function of sampling interval and serves as an ex ante estimate of the sampling interval impact. To develop the uncertainty indicator, we utilize a historical time-series of precipitation, runoff, sedimentation, and pollutant (i.e. P) data.

The contribution of this work is best viewed in the context of a comprehensive management approach when several stakeholders and catchments are involved in water quality protection plans. To implement and enforce management plans, extensive spatial and temporal data collection is needed which requires substantial financial and labor investments. Therefore, the proposed welfare analysis can provide decision-makers with information related to the stakeholder preference (or willingness-to-pay) to collect additional information.

Background

Nutrient export coefficients

The nutrient export coefficient model suggested by Reckhow, Beaulac, and Simpson (1980) is designed to estimate the lumped annual loadings. Since then, several structural enhancements have been introduced to this basic model. These improvements can be grouped into two classes: (1) distributed sub-watershed level and (2) lumped watershed level. At the sub-watershed level, the watershed is divided to smaller units with tractable levels of information. For instance, Soranno et al. (1996) estimated the P loading considering attenuation with traveling distance and Wickham et al. (2003) considered the relative location of sub-watershed units within the watershed. As for the lumped models, Endreny and Wood (2003) modified the lumped annual form by integrating terrain and land use weighing factors to the basic model. The weighted EC was then used to identify the critical areas of NPS loadings.

Khadam and Kaluarachchi (2006a) suggested a modified form that includes the annual sediment loadings providing the capacity to assess hydrologic variability. Theoretically, sub-watershed models can produce better predictions; however, these models require intensive input data associated with significant uncertainty that will propagate through the model calculations and ultimately deteriorate the quality of final results (Jetten, Govers, and Hessel, 2003). Therefore, the benefit of using complex data intensive models may be diminished by data uncertainty and cause the complex models to perform poorer than the lumped regression models.

P export coefficients

P loading is an important quantity in the NPS pollution assessment process (Stumborg, Baerenklau, and Bishop, 2001). Therefore, in this study we focus on the TP loading estimations using a lumped export coefficient model. P is transported to water bodies mainly via surface runoff (McDowell and Sharpley, 2001).

A detailed description of P transport and its interactions can be found in Sharpley et al. (2002) and McDowell et al. (2001). EC represent the average annual amount of nutrient loaded into a system from a defined area. EC are reported as a mass of pollutant per unit volume of water. The basic form of phosphorus EC estimates the annual P loads to water bodies from a catchment as the sum of individual loads exported from each land use type and given as

$$L=\sum_{i=1}^{M} E_i x A_i x I_i \tag{6}$$

where L is the annual P load (kg); E_i is the export coefficient from land use i (kg/ha-yr); Ai is the watershed area occupied by land use i (ha); l_i is the P input from land use i (kg/ha); and M is the total number of land use classes.

The basic P-export coefficient (Equation 6) considers the annual P loading from land uses to the watershed outlet without considering controlling processes (Khadam and Kaluarachchi, 2006a). A major limitation of this basic model is that while it is sensitive to changes in land use area and P application rates; it ignores processes important for pollutant transport, namely, runoff and soil erosion (Khadam and Kaluarachchi, 2006a).

An alternative formulation of P-export coefficient suggested by Khadam and Kaluarachchi (2006a) considers these sources of uncertainty which is given as

$$L_{\Phi}=\Phi(R)\sum_{i=1}^{M} K_i x A_i x I_i \tag{7}$$

where R is the annual runoff (m^3); Φ(R) is the annual sediment discharge as a function of annual runoff (kg); and the term $K_i=(E_i/\Phi(R))$ represents the erosion-scaled P-export coefficient of land use i (kg/L).

The sediment-adjusted EC (Equation 7) has the advantage of maintaining low data requirements compared to spatially distributed models while improving the prediction accuracy of observed loadings as illustrated by Khadam and Kaluarachchi

(2006a). The annual export coefficient is frequently used to compute a lumped annual estimate of pollutant load (NRC/NAS, 2001) which provides the basis for comparison with empirical estimates in the literature. Hydrologic variability is explicitly represented in Equation (7) with a parameter for sediment load which is a function of runoff.

Water quality prediction

Water quality predictive models are categorized as mechanistic or empirical models (Reckhow, 1994). Mechanistic models are process based and require calibration and verification. In contrast, empirical models are data driven and focus on examining the trends of observed data. Due to the nonlinear behavior of water quality parameters in this work, we utilized sparse bayesian regression. Bayesian regression models such as Support Vector Machines (SVM) and Relevance Vector Machines (RVM) view data as a chaotic system in which data series are assumed to provide enough information about the behavior of the system to perform forecasting (Khalil et al., 2005).

Support vector machines provided good performance in several water resources applications (Khalil et al., 2005); however, the support vector machines predictions are not probabilistic (Muller et al., 2001). Unlike support vector machines; RVM are based on a probabilistic Bayesian learning framework (Tipping, 2001).

RVM are distinguished among other regression models by its capacity to consider uncertainty in both data and parameters (Khalil et al., 2006). RVM simplifies complex systems by producing “structured” models; therefore parameterization process fits the information content. The key advantage of RVM is the generalization ability and the sparse formulation of the resulting model that utilizes few kernel functions (Khalil et al., 2006). RVM fits naturally into a regression framework and yield full probability distributions of the output. It is beyond the scope of this study to provide a detailed description of RVM and interested readers are referred to Tipping (2001) and Khalil et al. (2006).

Methodology

The conceptual approach proposed here is based on the environmental choice modeling suggested by Hanely, Mourato, and Wright (2001) and adapted here to estimate the benefit of decisions on collecting additional temporal data. A flow chart of the general process which can be modified for other applications is illustrated in Figure 14.

Due to its abstract nature, the proposed conceptual framework is best illustrated in the context of a selected application. The general framework (Figure 14) is represented by the following modules: (1) *information level realization*; (2) *information level impact assessment*, and (3) *the welfare impacts of additional information*.

We provide a practical framework as shown in Figure 15 to implement the general framework in the context of P loading.

Modules 1 and 2 are designed to support the welfare analysis presented in Module 3. It is assumed that hydrologic variability is consistent in time and space at the regional level. Therefore evaluation of one catchment can predict hydrologic variability at the regional level for a desired period.

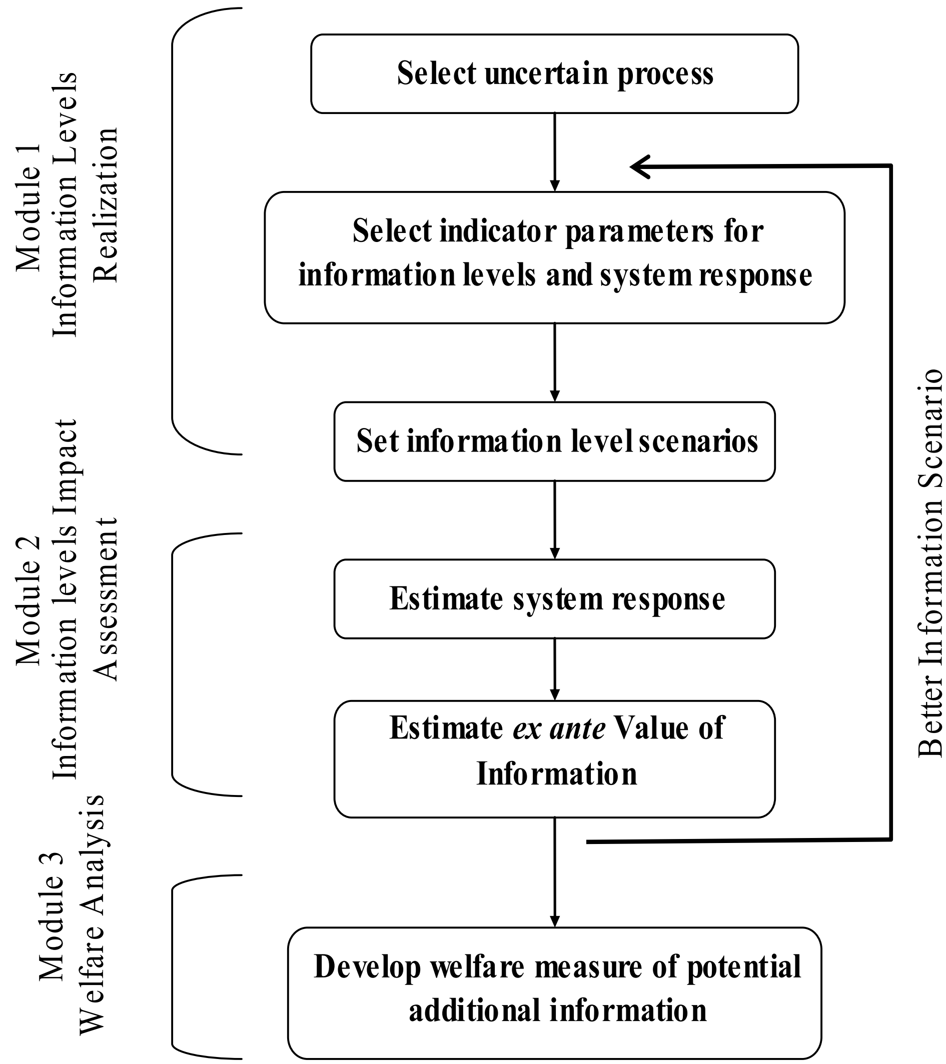

Figure 14. A schematic showing the conceptual framework of the proposed methodology.

To develop the *ex ante* estimates of information levels; we assume that the hydrologic variability for a given region is captured in the historical data sets which is valid as long as no significant changes in land uses and climatic conditions are observed.

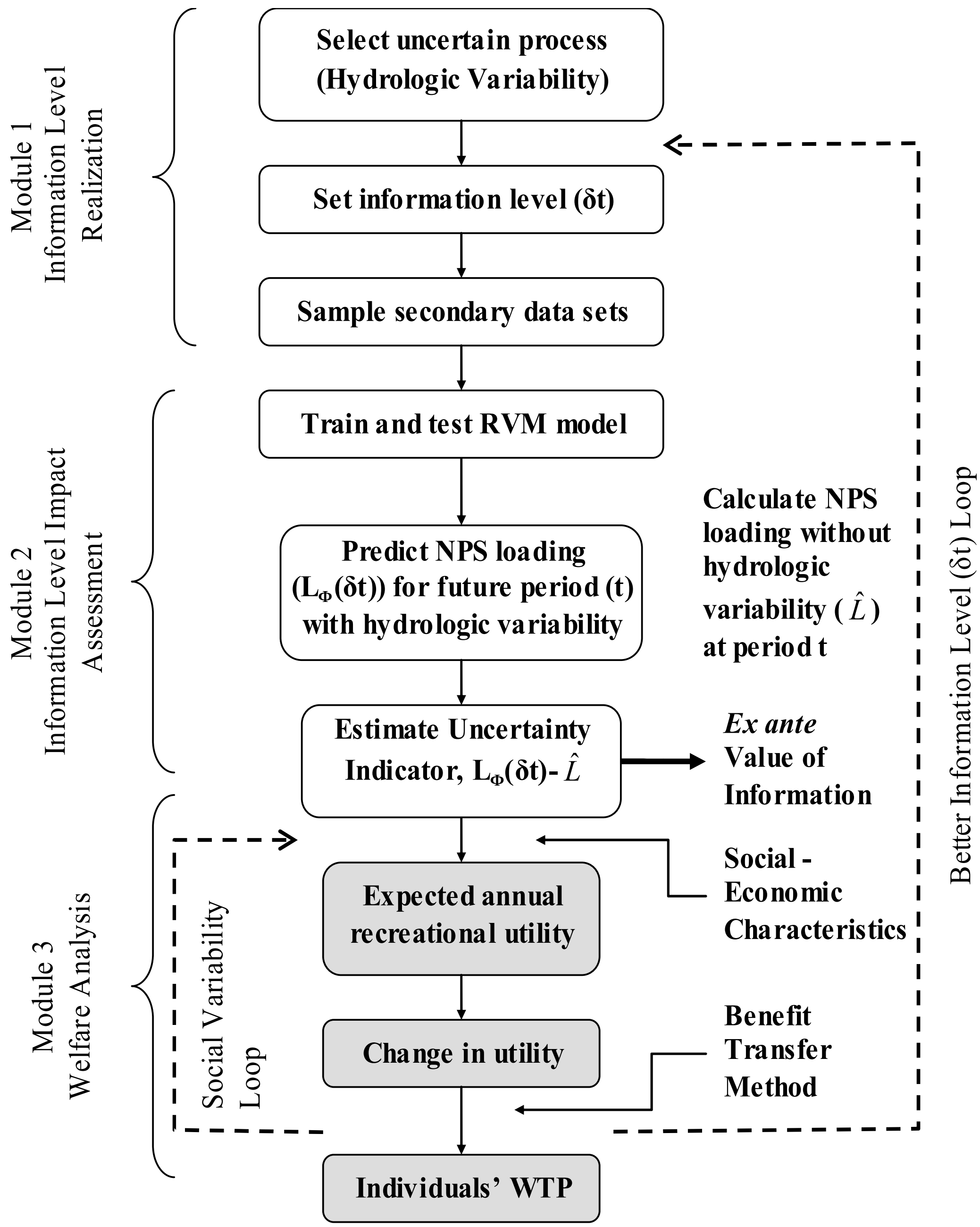

Figure 15. A detailed layout of the proposed framework showing the three modules and the supporting analyses.

The benefit of these assumptions is that unmonitored catchments under similar land uses and climatic conditions would have similar hydrologic variability as the representative catchment.

<u>Module 1: Information level realization</u>

Consider that historical data of pollutant loadings for a given watershed captures hydrologic variability for a given region. Therefore, a historical record can provide the basis to estimate hydrologic variability for a given watershed and therefore for a region. Today, sufficient water quality data records are available through several agencies and data banks. The historical data hereafter referred to as the baseline data set is composed of time-series of precipitation, runoff, sediments, and P loading.

Using the assumption of a steady hydrologic variability pattern in time; we can predict the future loadings using the baseline data set. For this purpose, information level scenarios are produced by sampling the baseline data set at different sampling intervals (δt) ranging from the smallest to the largest interval. δt determines the sampling frequency and it provides an indication of uncertainty due to hydrologic variability. As the sampling interval is reduced (at higher sampling frequency); hydrologic variability is characterized with higher accuracy. The proposed sampling process produces different sets of time-series data (from the baseline set) at selected δt which are used as inputs to estimate the hydrologic variability impacts in Module 2.

<u>Module 2: Information level impact assessment</u>

The goal of this module is to express the impact of uncertainty of P loading due to hydrologic variability that was overlooked between sampling events. There is a need to quantify the impacts of uncertainty in a sensible measure that is useful in the welfare analysis. Here we develop uncertainty indicator that links the data collection level (given as δt) to the expected P loadings. This proposed uncertainty indicator is consistent with the value of information analysis approach (Borisova et al., 2005) and provides an ex ante estimate of undetected pollutant loadings. The uncertainty indicator E(x(δt)) is defined as

$$\textit{Uncertainty Indicator} = E(x(\delta t)) = E(L_{\Phi}(\delta t)) - \hat{L} \tag{8}$$

where $E(L_{\Phi}(\delta t))$ is the expected TP loading with hydrologic variability and $\hat{L}$ is the TP loading without hydrologic variability at a given time. The value of $E(L_{\Phi}(\delta t))$ is computed with the aid of each constructed data series corresponding to a sampling interval δt described in Module 1. For example, each data series of sampling interval δt constructed from baseline data is trained and tested using RVM consisting of observed precipitation, runoff, and sediment data. Once the RVM is developed, the sediment and runoff values can be computed at a future time period. Once runoff and sediment are known at this future period, the erosion-scaled EC can be found and then Equation (7) can be used to compute the corresponding TP loading. This load $E(L_{\Phi}(\delta t))$ now represents hydrologic variability. The value of TP loading without hydrologic variability $\hat{L}$ is computed directly using Equation (6).

The reason for computing the value at a future time is, typically, policy decisions related to water quality mitigation is performed for a future period. Therefore, willingness-to-pay (WTP) of stakeholders for a future mitigation event can be computed. An iterative algorithm was developed to optimize RVM parameter selection (kernel function type and width). Model performance for each constructed data set is evaluated for training and testing phases using bias, mean absolute error (MAE), root mean square error (RMSE), and index of agreement (IoA). In summary, the output used in the welfare analysis is a set of uncertainty indicator estimates $E(L_{\Phi}(\delta t))$ calculated using Equation (8).

A major advantage of the proposed approach is its transferability to a new setting (i.e. watershed). Typically, for a new watershed, a new learning process involving training, testing, and validation is needed for the constructed data sets. The uncertainty indicator (undetected pollutant loadings) provides an explicit measure of the adverse effects on receiving water bodies due to uncertainty arising from gaps in data collection.

Module 3: Welfare analysis

Module 3 estimates the socioeconomic value of collecting additional information. We utilize a recreational demand model to estimate individuals' utility based on his/her recreational activity which depends on the state of receiving water bodies. The analysis is limited to recreational fishing behavior as a proxy of demand on recreational uses to estimate utility levels matching different risk levels posed by undetected P loadings. Then, we estimate the WTP to reduce this risk using a recreation benefit transfer model. WTP is estimated by comparing two pollution risk levels for two decisions reflecting different data collection levels (or δt). Thus, comparing any two risk levels produces the societal benefit estimate of acquiring additional information to reduce the risk of shock TP loadings to water bodies. Moreover, individual variability is recognized since for the same change in water quality, individuals indicate heterogeneous responses (Whitehead, 1995).

The welfare analysis benefits from related work in the literature. For the recreational demand model, the work of Leeworthy et al. (2005) was used to simulate the frequency of recreational fishing visits. The approach suggested in Smith et al. (2000) and Smith, Van Houtven, and Pattanayak (2002) was modified to estimate the WTP in this study. For this purpose, the household was defined as the economic unit and assumed that at least a fraction of its income is generated from some agricultural activity which will be adversely affected by any NPS management measure. The selection of the household level as the unit for economic analysis is attractive because it utilizes accessible social and economic data collected at the household level by several agencies. The household head is the utility maximizer and acts to reduce the risk of loss in income in the form of more stringent NPS regulations endured because of misclassified NPS loadings. We consider a target population with known characteristics such as income, household size, age, education level, and the number of visits to recreational fishing areas.

Recreational utility function. Numerous studies in the recreational economics literature used the Travel Cost Method to assess the environmental impacts on water relevant recreational values (Sandstrom, 1996; Smith, 1991; Wilson and Carpenter, 1999). The Travel Cost Method entails observing the time and money spent to visit a recreation site to estimate the WTP for such visits. The essence of the Travel Cost Method is to determine the statistical relationship between price (travel costs) and quantity (the number of visits). The established link between the demands to a site and the quality of fishing sites can be used to estimate the changes in economic value associated with changes of quality of a water body. The Travel Cost Method utilizes data of environmental parameters (i.e. fish stocks) and social parameters such as the number of visits, distance traveled, or costs incurred.

The theoretical basis of the Travel Cost Method is the Household Production Function (HPF) to estimate the demand on recreational sites (Sandstrom, 1996; Smith, 1991) where the sources of utility are activities that the household produces from other inputs (Randall, 1994). The HPF method uses observed behavior as the basis for valuation, and non-use values such as species habitat are not observed. The HPF approach is sufficient to assess the changes in water quality for this study because fishing and recreational uses are major activities of the target population. The underlying assumption of the HPF is that a household allocates a fraction of its income and labor time to an activity that is affected by environmental quality. By determining how changes in environmental quality influence the HPF and the welfare of the household; one can estimate the gain in welfare due to better information scenarios.

In the context of recreational use evaluation, the HPF can be formulated as a random utility maximization model (Sandstrom, 1996). The primary reason for the popularity of this model is its capacity to depict individuals' decision-making process (Greene, Moss, and Spreen, 1997). The goal of the utility function is to represent the change in individuals' welfare in response to changes in quality of environmental resources. The TP loadings are linked to a preset information collection scenario, and the fishing visitation frequency is controlled by a vector of population attributes. Due to the small scale of the study area described here, we assume that a single water body is affected by TP pollution and the travel distance and cost are marginal due to close proximity. We used a random utility model similar to the one described by Train (1998) for recreational fishing uses.

The utility (U) obtained from a visit by an individual n who is also the household head is given in Train (1998) as follows:

$$U_n = \beta_n x_n + e_n \tag{9}$$

where x_n is a vector of observed explanatory variables (i.e. age and income); β_n is a vector of unobserved weighing coefficients for each individual n that varies randomly representing each household taste; and e_n is unobserved random error term that is identically and independently distributed extreme value, independent of β_n and x_n.. Train (1998) suggested that coefficients β_n vary with population and is defined as $\beta_n = b + \eta_n$, where b is the population mean and η_n is the individual deviation which represents the taste of individual n relative to the average taste of population. Train (1988) suggested correlating a portion (η_n) to recreational site characteristics. The term η_n drops when considering a single recreation site. Train (1998) suggested selecting a distribution or a fixed value for β_n that is appropriate to population anticipated behavior related to a given variable, x_n.

In this analysis, we propose a practical utility function based on Equation (9) that incorporates the undetected TP loadings as a proxy of environmental impacts, and recreational fishing visitation frequency as an aggregate parameter of individual characteristics (age, income, and education level). The premise of this utility function is to estimate the gain in utility if improvements in data collection is considered at a given baseline data collection level. When additional data collection is considered; the utility increases if more undetected loadings are uncovered because the benefits to water quality protection are high. Also, gain in utility for an individual with more visits per year is higher than the case of fewer visits. The proposed utility function given in Equation (9) is presented as an expected value of predicted TP loading estimates from the RVM model in Equation 10 as follows

$$E(U_n) = \beta_1 \cdot E(x\ (\delta \mathrm{t})) + \beta_2 \cdot x_{VISIT(n)} + e_n \tag{10}$$

where β_1 and β_2 are weighting coefficients and $x_{VISIT(n)}$ is the number of visits to the site by individual *n*. We assume that individuals respond equally to the two portions of the utility function. Therefore, we consider β_1 and β_2 to be equal with a fixed value of 0.5 for each.

To sustain transferability of the methodology and to accommodate the target population properties; we used a calibrated socioeconomic visitation model at the US regional level. We utilized the calibrated visitation models in the National Survey on Recreation and the Environment of 2000 prepared by Leeworthy et al. (2005) for the regions of the US. Leeworthy et al. (2005) calibrated a negative lognormal model that analyzed population visitation behavior using socioeconomic variables such as age, income, and education level for the US at a regional scale. Leeworthy et al. (2005) proposed the model to estimate x_{VISIT} (in days per year) as

$$x_{VISIT} = \exp(\rho + \sum \mu_k x_k) \tag{11}$$

where ρ is a model constant; x_k is a variables for socioeconomic attributes (age, income, and education); and μ_k is a coefficients for the socioeconomic variables (different for each activity). Equation (11) estimates average days of fishing visits per person of 16 years and older. The estimates of visitation frequency (from Equation 11) are used as an input in Equation (10). In summery, the utility formulation (Equation 10) is simple yet it is sufficient because it explicitly represents the environmental change and implicitly integrates key household attributes that affect the recreational visitation frequency.

Benefit transfer for WTP estimation. The next step in the welfare analysis is to estimate the WTP of the target population to obtain higher utility as a result of a potential improvement in information collection. The theoretical basis of WTP for quality improvement entails that the WTP is a function of pre-policy and post-policy quality levels (Mitchell and Carson, 1989; Smith et al., 2000). In this analysis; a preference calibrated BTM is employed to construct an accurate benefit transfer model for a new setting using reported estimates from contingent valuation studies. To estimate recreational fishing benefits; Smith et al. (2000) and Smith, Van Houtven, and Pattanayak (2002) described a procedure to apply the benefit transfer approach to estimates of WTP for water quality improvement for a new setting. It is beyond the scope of this study to reiterate the theoretical basis of the BTM which is discussed by Smith et al. (2000), and Smith, Van Houtven, and Pattanayak (2002). Instead, we concentrate on the derivation of WTP formulation, proposed modifications, and the practical aspects of WTP estimation. In this analysis, a WTP formulation that integrates individual perception related to water quality protection is developed.

The BTM begins by developing a preference calibration structure to describe individual preferences related to water quality and recreational fishing. Smith, Van Houtven, and Pattanayak (2002) suggested a preference structure consistent with the assumption of Willing (1978) which implies that an indirect utility function (V) is structured so that the water quality measure reduces the effective price of using the recreation sites. The original V function is given as

$$V = \left[\left(p - h\left(L_{TP}\right)\right)^{-\hat{\alpha}} \cdot m \right]^{b} \tag{12}$$

where p is the price of round-trip travel costs for a recreation visit (\$/ roundtrip); m is household income (\$/yr); $\hat{\alpha}$ and b are coefficients; and $h(L_{TP})$ is a function that describes how improvements in water quality reduce the effective price of a trip (\$/roundtrip). Water quality is measured as TP pollutant loading (L_{TP}) which is estimated earlier in Module 2 as the uncertainty indicator. Therefore, we can define L_{TP} as $L_{TP} \equiv E(x(\delta t))$ in kg/yr.

In this analysis, population heterogeneity is considered in the derivation of the WTP formulation. Therefore, the original indirect utility function (Equation 12) which provides the basis to derive the WTP is re-evaluated and modified to represent population variability. Population variability in income can be represented by sampling incomes using the Monte Carlo approach from specific distributions of the target population to develop individual income (m_n). The function $h(L_{TP})$ is a major concern for this analysis because it determines the impact of incremental improvements of water quality. In Smith et al. (2000) and Smith, Van Houtven, and Pattanayak (2002), the authors imply that $h(L_{TP})$ is not affected by population variability which represents an oversimplifying assumption that is inconsistent with the scope of this work. The implication of this assumption is that a given improvement in water quality has an equal impact across individuals in terms of visitation frequency which determines the effective price using the term $(P - h(L_{TP}))$. Also, the function $h(L_{TP})$ describes the marginal change of price of fishing trip (*p*) with water quality and ignores other non-market values such as the existence value. Another complication for the transferability of $h(L_{TP})$ to a new setting is that it is unobservable and it is estimated implicitly. To estimate $h(L_{TP})$, an indirect procedure (discussed below) is applied which assumes an appropriate $h(L_{TP})$ structure and using reported estimates from relevant empirical studies which are difficult to replicate in a new location.

Hence, to represent the individual variability in a theoretically sound and a practical manner and to sustain transferability, we propose to incorporate the expected recreational utility calculated in *Module 2* ($E(U_n)$) as a measure of population variability in Equation (12). To formalize this modification; the original water quality term $h(L_{TP})$ is multiplied by $E(U_n)$. In essence, the integration of individuals' income (m_n) and recreational utility ($E(U_n)$) with the water quality parameter represents social perception explicitly and produces individual–specific estimates of calibration terms $\hat{\alpha}_n$ and b_n and indirect utility (V_n). The modified *V* formulation for individual *n* is provided below as

$$V_n = \left[\left((p - h\left(L_{TP}\right) \cdot E(U_n) \right)^{-\hat{\alpha}_n} \cdot m_n \right]^{b_n} \tag{13}$$

where subscript *n* defines the terms that are variable across individuals. For the remaining analysis, we follow the same procedure described by Smith et al. (2000) and Smith, Van Houtven, and Pattanayak (2002) to derive and calibrate the WTP formulation using the new combined term ($h(L_{TP}) \cdot E(U_n)$) instead of the original $h(L_{TP})$. Except for this new term, the proposed formulation is identical to the original work of Smith et al. (2000) and Smith, Van Houtven, and Pattanayak (2002).

Estimation of $h(L_{TP})$ begins by assuming an appropriate function for $h(\cdot)$ which is represented as a power function with a declining marginal effect of pollution on the price (Smith et al., 2000; Smith, Van Houtven, and Pattanayak, 2002). $h(L_{TP})$ is defined as $h(L_{TP}) = \left[L_{TP}\right]^{\beta}$ and its first derivative is expressed as $h'(L_{TP}) = \beta(L_{TP})^{\beta-1}$. The Marshallian Consumer Surplus (MCS) is a common welfare measure of change in welfare related to the change in effective price that is determined by water quality. The empirical estimates of MCS can be obtained from the contingent valuation study of Englin, Lambert, and Shaw (1997) where the increase in MCS per fishing trip is equivalent to the first derivative of $h(L_{TP})$ as shown in Equation (14).

$$\frac{\partial MCS}{\partial L_{TP}} \Big/ c_1 \equiv h'(L_{TP}) = \beta(L_{TP})^{\beta-1} \tag{14}$$

The term c_1 is defined as the demand for fishing trips estimated using the common Roy's identity and expressed as the number of visits/yr. The left term of Equation (14) is obtained empirically and it represents how MCS changes with L_{TP} . Practically, the coefficient β is recovered using known L_{TP} from Module 2 and the estimated left term of Equation (14) using empirical estimates from Englin, Lambert, and Shaw (1997). In their study, Englin, Lambert and Shaw (1997) linked dissolved oxygen levels which are analogues to NPS loading, total fish catch, and travel cost demand model to produce estimates of MCS for known improvements in dissolved oxygen levels in lakes in the eastern US in 1989.

We assume that the reported estimate of parameter β by Smith, Van Houtven, and Pattanayak (2002) is sufficient for this recreational fishing study and elsewhere because β is based on the risk levels posed to fishing resources rather than the type or source of risk. Smith, Van Houtven, and Pattanayak (2002) estimated β to be \$35.64 for 1995 which is adjusted in for this analysis to \$45.50 for the year 2000. Now, we can define $h(L_{TP})$ in the following analysis after β is determined.

To estimate $\hat{\alpha}$ at the individual level n ($\hat{\alpha}_n$); a bench mark WTP estimate ($W\hat{T}P$) is selected from a comparable study and used with p, m_n, water quality at baseline (L_{TP}^0), and improved data collection (L_{TP}^1) levels as given below:

$$\hat{\alpha}_n = \ln\left(\frac{m_n - W\hat{T}P}{m_n}\right) \Bigg/ \ln\left(\frac{P - h(L_{TP}^1)\cdot E(U_n)_1}{P - h(L_{TP}^0)\cdot E(U_n)_0}\right) \tag{15}$$

Note that Equation (15) now produces utility-adjusted $\hat{\alpha}_n$ which is an enhancement over the original formulation of $\hat{\alpha}_n$. The original WTP (from the baseline 0 to new information level 1) suggested by Smith et al. (2000) and Smith, Van Houtven, and Pattanayak (2002) is given below:

$$WTP_n = m_n - \left[\frac{(P - h(L_{TP}^1))}{(P - h(L_{TP}^0))}^{\hat{\alpha}_n}\right] m_n \tag{16}$$

where WTP_n is the WTP for improving data collection from baseline (level 0) to better information (level 1). The WTP estimation using Equation (16) does not adequately represent the population variability in the evaluation of change in water quality. The proposed WTP formulation is given below

$$WTP_{n(0,1)} = m_n - \left[\frac{(P - h(L^1_{NPS})) \cdot E(U_n)_1}{(P - h(L^0_{NPS})) \cdot E(U_n)_0}^{\hat{\alpha}_n} \right] m_n \tag{17}$$

This formulation of Equation 17 is slightly different from Equation 16. The proposed formulation has the advantage of using utility-adjusted $\hat{\alpha}_n$ and $h(L_{NPS})$ that are individual specific due to the proposed modification of integrating $E(U_n)$ in the derivation of $\hat{\alpha}_n$ and WTP_n.

Equation (17) represents population variability in $h(L_{NPS})$ which is assumed to be fixed across individuals in the original WTP formulation. Therefore, Equation (17) provides higher accuracy and more robust representation of population variability than the original WTP formulation. The proposed WTP formulation (Equation 17) is applied in the context of Monte Carlo sampling of specific distributions of target population characteristics to estimate the visitation frequency using Equation (11) which is used with L_{NPS} to estimate recreational utility using Equation (10). Then the parameter $\hat{\alpha}_n$ is calibrated using Equation (15) and finally the WTP is estimated using Equation (17).

Management Application

Description of study area

The Water Resources Inventory Area (WRIA) 1 is located in the northwest corner of Washington State. The Nooksack River basin is located in Whatcom County of WRIA 1 covering an area of 825 square miles. The lowlands area is the focus of collaborative efforts by local, tribal and state officials to improve water quality (Hood, 2000).

Deteriorated water quality caused direct economic impacts such as closures of shellfish beds due to unsafe levels of bacterial pollution at nearby Puget Bay in 1998 (Hallock, 2002) and the disruption of recreational uses (Embrey, 2001). Related studies indicate that agriculture, dairy farming, and waste lagoons contribute the most to the observed elevated pollutant levels (i.e. nitrogen, phosphorus, and coliforms) in the Noocksack River Basin (Carey, 2002; Hallock, 2002; Kaluarachchi and Almasri, 2002; Matthews, Hilles, and Pelletier, 2002).

Fishtrap Creek Catchment. Fishtrap Creek Catchment shown in Figure 16 is a representative watershed of the lower Nooksack River Basin. Fishtrap Creek is a small agricultural dominated catchment (95 km^2). The Fishtrap Creek Catchment provides habitat for a variety of fish species and it is identified as a major source of bacterial loadings and regulated by a bacterial TMDL plan. A comprehensive review of the state of water quality management in the Fishtrap Creek is provided by Almasri and Kaluarachchi (2004) and Khadam and Kaluarachchi (2006a). Fishtrap Creek is characterized by intensive agricultural and dairy production.

The NPS loadings in Fishtrap Creek are mainly attributed to fertilizer application and manure storage. The urban pollutant loadings from the cities of Abbotsford and Lynden are diverted to streams other than the Fishtrap Creek; therefore, the contribution of urban loadings is limited. In the Nooksack River Basin, protection of fish habitat and recreational fishing are major challenges for stakeholders (Joy, 2000). Therefore, reducing the risk of undetected NPS loadings have a positive effect. The observed TP concentration of Fishtrap Creek frequently exceeded the US EPA limit of 0.1 mg/L

(Khadam and Kaluarachchi, 2006a); therefore, the focus on TP loadings as a proxy of NPS pollution is justified.

Results and discussion

Originally, the Fishtrap Creek outlet (Station A in Figure 16) has a short data record for the period from 1996 to 1998; however, Khadam and Kaluarachchi (2004) reconstructed water quality data for the Fishtrap Creek outlet using an interior upstream point with a data record covering the period from 1987 to 2001 using support vector machines. A period of three-year overlap in data collection between the two points (1996-1998) was used to calibrate and verify the performance of SVM model.

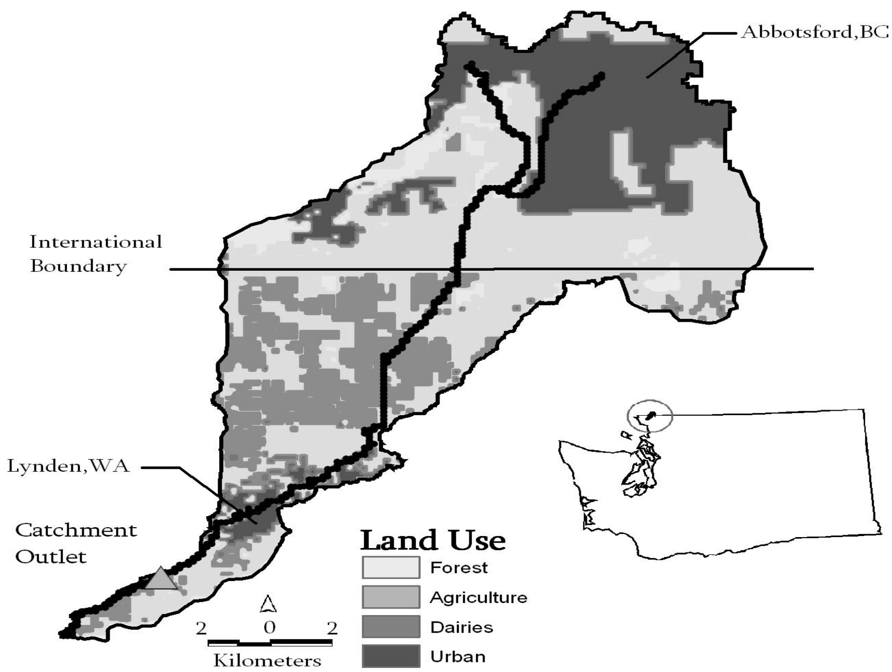

Figure 16. The layout of Fishtrap Creek Catchment showing land-use types and the location of the catchment outlet (Station A).

The reconstructed data set showed high prediction performance during calibration and verification with an average bias of 6%, MAE of 0.003, and a correlation coefficient of 0.995 (Khadam and Kaluarachchi, 2004). Therefore, the reconstructed data for Fishtrap can be used with confidence.

The baseline data used here are daily records from 1987 to 1998 at the outlet of Fishtrap Creek Catchment (Station A in Figure 16) and includes precipitation (cm), runoff (cm), sediment loadings (kg), and TP loading (kg). The observed TP loading of Fishtrap Creek (shown in Figure 17) indicates frequent shock loading events which exemplify the importance of intensive sampling to capture hydrologic variability of the catchment. Intuitively, at a low sampling frequency; less data is collected and the probability of missing important loading events due to hydrologic variability is higher which means a higher risk of harmful undetected loadings to water bodies.

Data collection scenarios (Module 1). Using the baseline data with daily time steps; a series of data sets were derived at discrete and increasing sampling intervals ranging from 2 days to 120 days to simulate long-term data collection scenarios. The total number of data time-series derived was 40. The 2-day sampling reflects the most accurate while the 120-day interval corresponds to the least accurate scenario.

RVM application (Module 2). The *Matlab* application of RVM suggested by Tipping (2001) was used here to develop the RVM model. This approach was successfully used in several previous water resources applications (Khalil et al., 2005) too.

For each data set derived from the baseline set corresponding to a given δt, training and testing were conducted. Upon a successful calibration and verification process; the error in prediction using the RVM model can be attributed to the data collection scheme with a given δt. The indigenous error in prediction due to model related sources is neutralized by considering the difference between two simulated scenarios.

The excellent RVM performance is obtained using a gaussian basis function with a band width of 4.0 for all secondary data sets with an average bias of 0.005, RMSE of 0.4, MAE of 0.30, and IoA of 0.91. The details of training and testing results are given in the Appendix.

Impacts of data collection levels (Module 2). The calibrated RVM models were used to predict the TP loading for the year 2000. The uncertainty indicator (expected undetected TP loading) is calculated for that year using the best estimate of TP loading

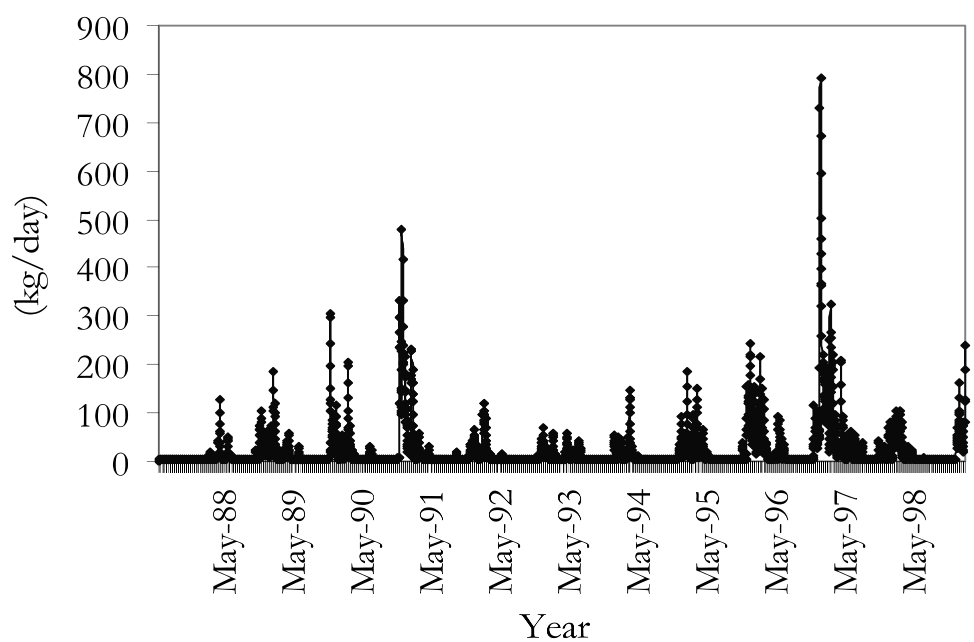

Figure 17. Daily time-series of TP loading at Station A of Fishtrap Creek Catchment.

(from Equation 6) which employs standard EC and land use profile for the year 2000. The input variables used to estimate the P loadings for Fishtrap Creek are summarized in Table 5.

The uncertainty indicator signifies the *ex ante* impact of a potential decision of using a given data collection level and it is used as input in the welfare analysis. As shown in Figure 18, the uncertainty indicator or undetected TP loading decreases as data collection is improved with shorter sampling interval.

Visitation model (Module 3). The economic analysis was conducted for a representative population of the study area that was generated using Monte Carlo sampling of specific distributions of related variables of the target population. The simulated population represents 1,000 households of Lynden City.

Probabilistic distributions of population age classes were obtained and the appropriate age-dependent distributions of income and education levels were prepared for the year 2000 (US Census Bureau, 2000).

Table 5. Export coefficients used to estimate P loading for the Fishtrap Creek Catchment using Equation (6); Sources, Khadam and Kaluarachchi, (2006a)

Land use	**Basic EC (E_i)**	**Area (ha)**	**P loading rate (kg/ha)**	**TP loading (kg)**
Agriculture	0.025	4896	30	151,739
Urban	0.02	2397	1.8	4267
Forest	0.02	836	1.6	1355
Dairy	0.035	1381	167.8	23,1668
Total		*9510*		*389,029*

The calibrated lognormal visitation model for the pacific region as described in Table 6 was utilized with the distributions of related social variables to estimate the visitation frequency using Equation (11). To evaluate the validity of estimated visitation frequency, we compared the simulated visitation with the best estimate reported in the literature for the target population. The simulated visitations indicate a median of 11 days which is slightly higher than the median estimate of 7.9 of Washington State.

Expected utility estimation (Module 3). The simulated number of visits and the uncertainty indicator estimates of year 2000 were used to estimate the expected utility gain using Equation (10). The expected utility function assumes that for a given baseline data collection level; any improvement in data collection has the potential to detect the full extent of undetected P loadings at that level.

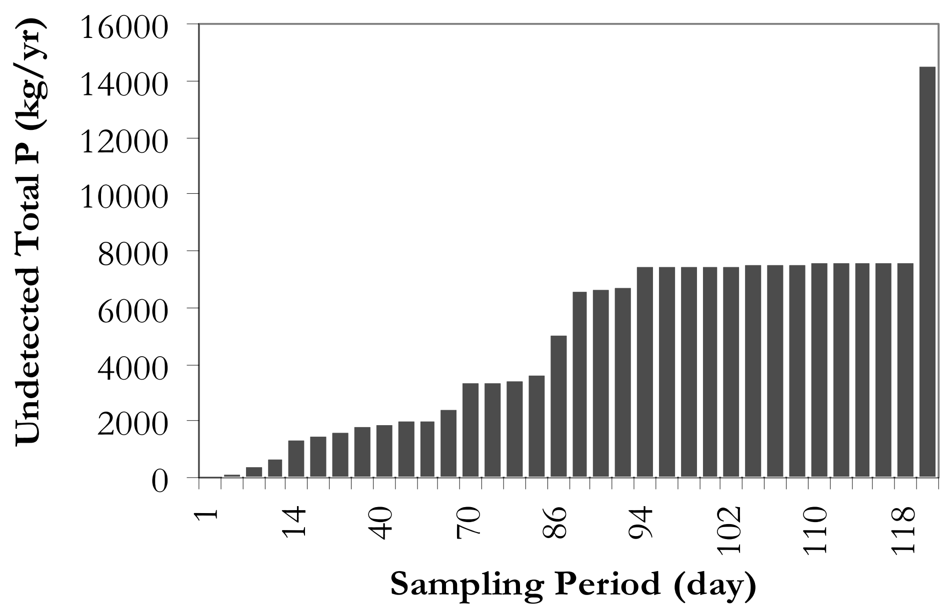

Figure 18. Predicted undetected annual TP loading (or *uncertainty indicator*) as a function of data collection level (sampling interval) for the Fishtrap Creek Catchment for year 2000.

For illustration, consider a baseline scenario A with low data collection level (large δt); the undetected loadings are high and therefore the benefit of additional sampling (expected utility) is expected to be high.

Similarly, consider a baseline scenario B with a high data collection level (short δt); the undetected loadings are low and therefore the benefit of additional sampling (expected utility) is low.

By comparing the two baseline scenarios A and B; one can estimate a gain in utility for a known improvement in data collection.

To illustrate the behavior of utility function; the population response for the full range of baseline data collection scenarios (from 1 day to 120 days sampling intervals) was estimated.

Table 6. Summary of empirical coefficients of the negative lognormal visitation model suggested by Leeworthy et al. (2005) for the Pacific Region including Washington State (US Census Bureau, 2000)

Population Variable (x)	**Coefficients**		**Data Type**
	ρ	***β***	
Household head age	-2.7617	-0.22566 (35-44) yrs. -0.438495 (45-54) yrs. -0.410361(55-64) yrs. -0.87735(>65) yrs.	Probabilistic distribution
Household head education		0.600268 (1=high school) 0.481914 (2=college) 0.313825 (3=graduate)	Age-dependent distribution
Annual household income		0.374579 (<$50,000) 0.311197 ($50,000-$100,000) 0.818227 (>$100,000)	Age-dependent distribution

The three-dimensional representation (Figure 19) shows the maximum expected utility level that an individual would gain if additional data collection is considered for a range of baseline data collection scenarios. In Figure 19, the x-axis represents the baseline sampling frequency as the sampling interval percentile (δt). The lower end of the x-axis (Figure 19) correspond to a short sampling interval which indicates highest baseline data collection scenarios, while the high end of the x-axis corresponds to long sampling intervals which reflects minimal data collection over time.

This pattern reflects decreasing marginal change which is consistent with the findings of Smith, Van Houtven, and Pattanayak (2002) and axioms of economic theory. The y-axis (Figure 19) represents the population variability percentile which reflects the population characteristics age, income, and education level. Since income and education levels are a function of age; the population variability is better explained by age.

The increase in variability percentile reflects an increase in population age. The lower percentiles represent young age groups and the higher percentiles represent old age groups. The observed trend of decreasing gain in expected utility as the age increases is attributed to the reduction in visitation frequency with age. This observation is in agreement with the trends of negative empirical coefficients reported by Leeworthy et al. (2005).

The impact of baseline information levels is better illustrated in Figure 20, where selected slices of the utility surface are shown along the population variability axis and across the baseline data collection level axis.

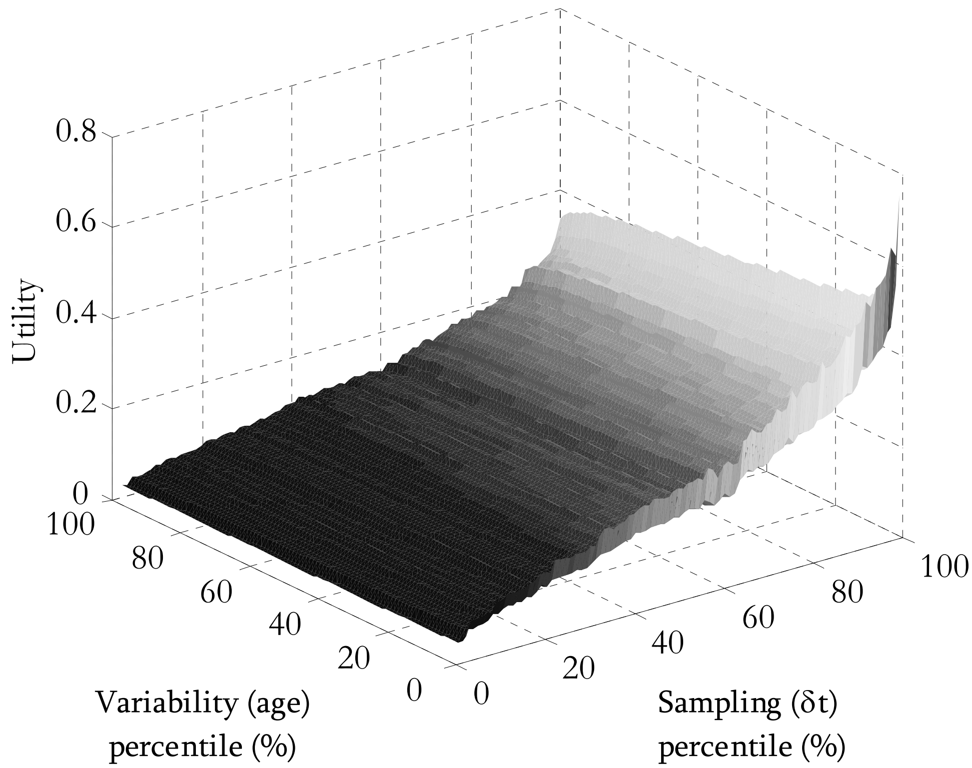

Figure 19. A three-dimensional depiction of expected utility as a function of baseline data collection (sampling interval) and population variability.

At any given population variability level; the potential utility gain decreases as the baseline data collection increases (lower δt percentile). At high baseline data collection levels (lower δt percentiles); the gain in utility diminishes for all population variability levels because the change in uncertainty becomes minimal which produces marginal effects at all ages.

Similarly, Figure 21 illustrates the impact of population variability levels on expected gain in utility at selected cuts of baseline data collection levels. For any given baseline data collection level, the gain in utility decreases as the variability level increases (in age).

However, we notice that variation along the sampling interval axis is higher than the variation across the population variability axis which indicates a significant impact of additional information on utility.

WTP estimation (Module 3). Several types of data and calculations are needed to estimate WTP using Equation (12). The individuals WTP assessment require calibration of parameter $\hat{\alpha}$ at the individual level using Equation (17). The cost of fishing trips (*p*) is estimated from the Economic Survey Pacific Cost of the year 1998 (RecFIN, 2001). The estimate for 1998 is $38 per trip and adjusted for year 2000 is $40 per fishing trip. The bench mark WTP value ($\hat{WTP}$) was obtained from Loomis (1996).

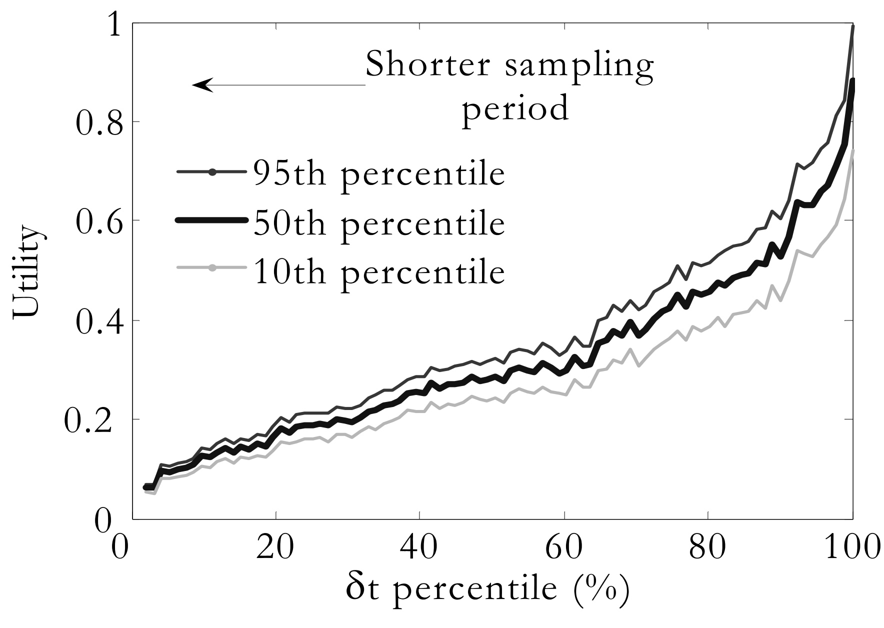

Figure 20. Selected cuts across various individual variability levels showing variation of expected utility with data collection levels.

Our review indicated that the WTP reported by Loomis (1996) is acceptable for this study because it represents recreators' valuation of fish stock protection in the State of Washington.

Loomis (1996) suggested a WTP value of \$78/household-yr for 1996 which is adjusted for year 2000 at \$94/ household-yr.

Using the Monte Carlo sampling of income distribution; individuals' income (m_n) was determined and the parameter $\hat{\alpha}_n$ was estimated at the individual level using Equation (17). The calibrated $\hat{\alpha}_n$ has a mean and a standard deviation of 1.74 and 0.004 respectively for the 1,000 sampled population of Lynden City. This steady value reflects low volatility of $\hat{\alpha}$ which provides confidence to any prediction made for water quality improvements.

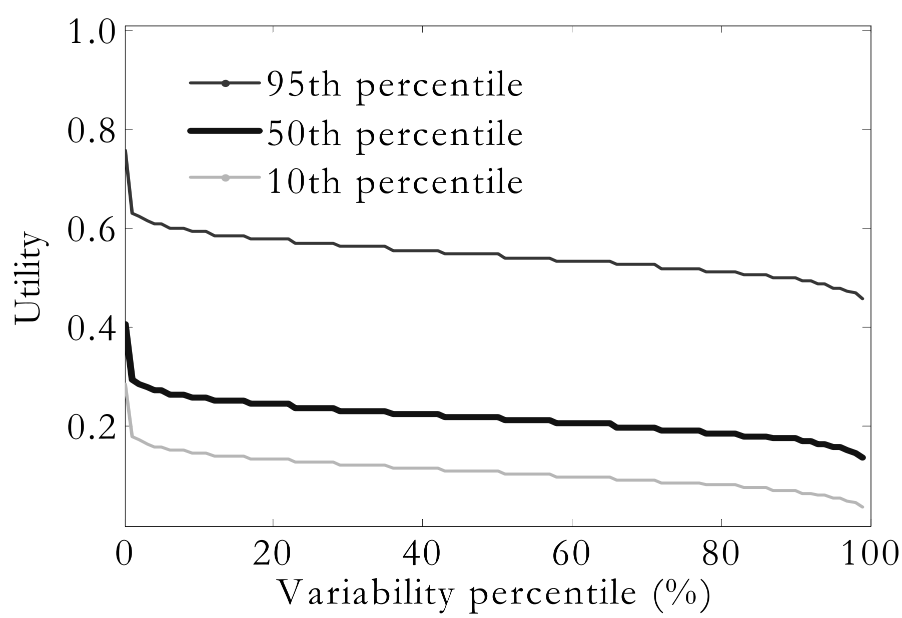

Figure 21. Selected cuts across various expected utility levels showing variation of individual variability with data collection levels.

Finally, the new WTP was estimated at the individual level using Equation (17) which compares two data collection levels. We estimate the individuals' WTP using the expected gains in utility estimates, utility-adjusted $\hat{\alpha}_n$, simulated population income, and the fixed value of trip cost. To illustrate the behavior of WTP function; the population response for the full range of data collection scenarios (from 1 day to 120 days of sampling interval) with population variability is shown in Figure 22.

The trends of WTP change is consistent with classical economic theory and observed patterns of the utility function behavior (Figure 19). As data collection levels increase (at lower δt percentile), the WTP to reduce uncertainty decreases. Also as the population variability (age) increases (at higher percentiles), the WTP decreases which is consistent with the findings of Pate and Loomis (1997).

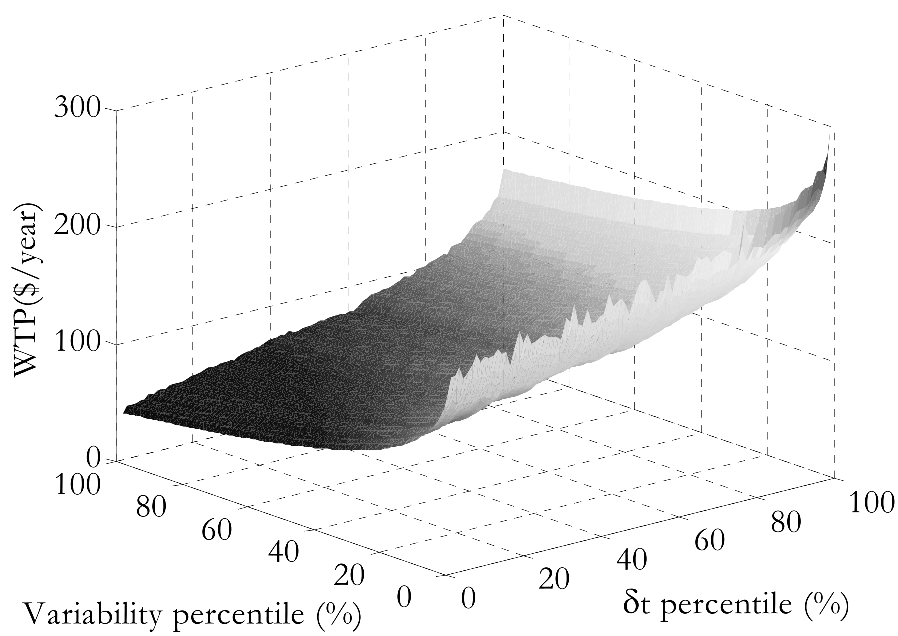

Figure 22. A three-dimensional depiction of households' WTP to obtain additional information as a function of population variability and data collection levels.

To better explore the trends of WTP change, a set of selected cuts in the WTP surface is shown in Figure 23. According to Figure 23, the WTP decreases as population variability (based on age) increases for selected baseline data levels.

Even though income and education may have opposite effects on WTP estimates; the structured Monte Carlo sampling of age-dependent distributions emphasize the effect of age which may conceal effects of other factors. However, the negative correlation between age and WTP is anticipated because of the negative correlation between age and visitation which is consistent with the findings reported by Dalton et al. (1998).

Figure 24 shows a set of cuts of WTP surface across the baseline data collection levels. For any population variability level; the WTP for additional information decreases at high baseline data collection levels because hidden TP loadings and expected benefits decrease with better data collection.

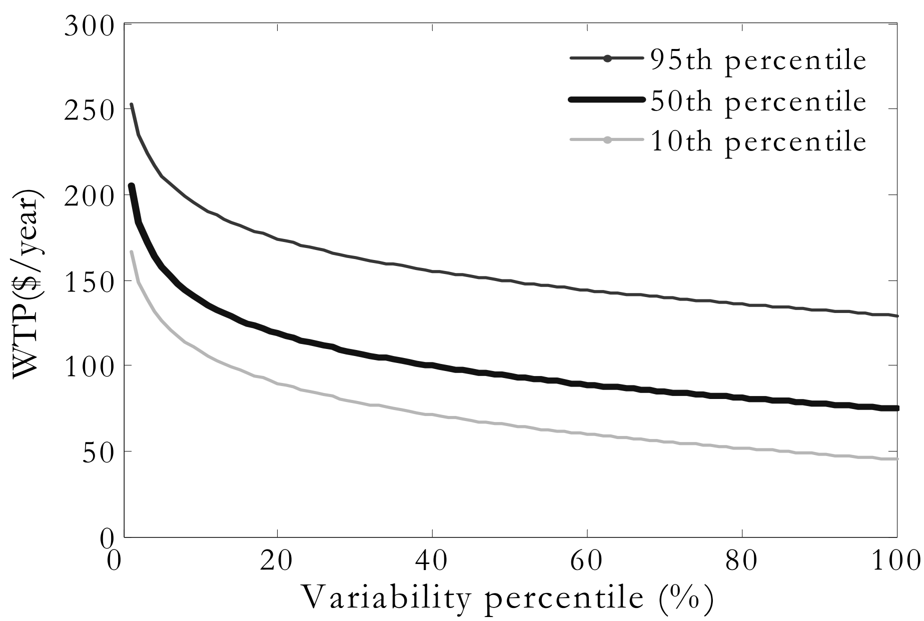

Figure 23. Selected cuts across different expected utility values showing the variation of household WTP with individual variability.

The WTP trend is consistent with the classical economic theory axioms and the observed utility trends.

Calculation example. The purpose of this calculation is to illustrate the significance of this WTP assessment in decision-making relevant to a management scenario. Two potential data collection scenarios for the Fishtrap Creek Catchment were considered and the details are shown in Table 7.

Consider a baseline data collection level with a minimal data collection at a 120-day sampling interval. The decision-maker is inclined to enhance the sampling program accuracy by increasing sampling frequency.

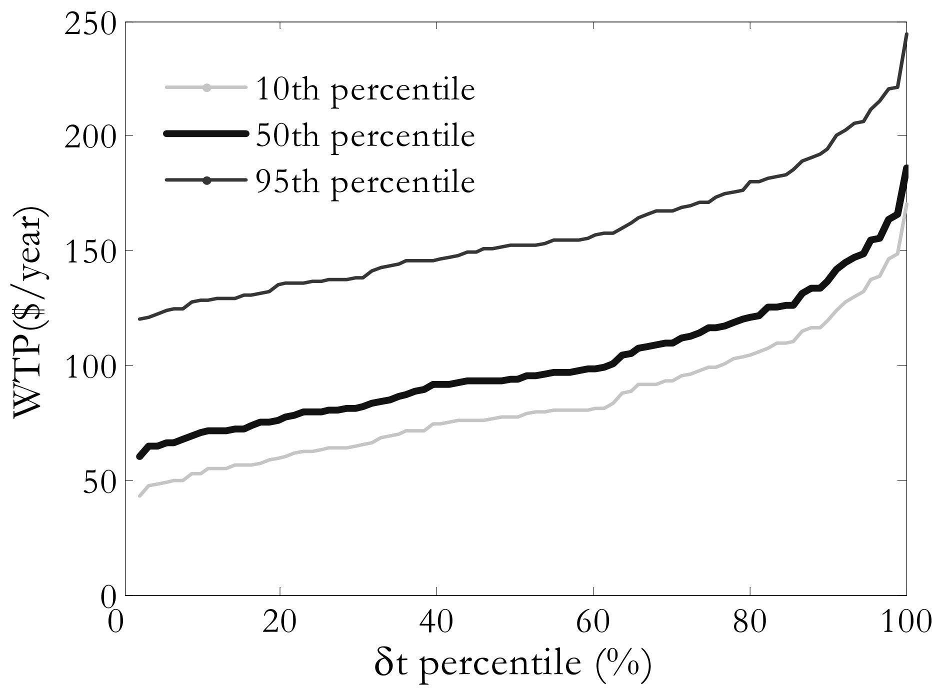

Figure 24. Selected cuts across different individual variability values showing the variation of household WTP with data collection scenarios.

However, the questions such as how much to invest, what is the WTP, the perceptions of the society, and what is the most efficient data collection strategy are not easily solved.

Consider two enhancement scenarios for a sparse sampling program; Scenario 1 is a 60-day sampling interval, and Scenario 2 is a 10-day sampling interval. The lower data collection level (60 days for Scenario 1) will have undetected loadings of 2,428 kg/yr which is three times higher than the undetected loadings at the higher data collection level (10 days for Scenario 2).

Therefore the improvement of 10 days sampling level would reduce the uncertainty (undetected TP loadings) by 1,761 kg/yr.

Next, the target population is informed of undetected TP loadings corresponding to each data collection level as the *ex ante* value of information. With the visitation frequency ($\boldsymbol{x_{visit}}$) estimated for the local population; the utility model detects a change in utility of 0.12 (from 0.26 to 0.14) in response to the better accuracy in TP loading assessment.

The mean annual WTP estimates of the improvements from Scenario 1 (δt =60 days) to Scenario 2 (δt =10 days) is $15 /year-individual to obtain 1,761 kg/yr reduction in undetected TP loadings based on the transferred estimate of Loomis (1996).

Summary and Conclusion

In this work, a new interdisciplinary socioeconomic methodology is proposed to assess the utility and WTP of a heterogeneous population to reduce uncertainty in NPS pollution due to hydrologic variability. The utility and WTP are assessed in terms of new information collection. The proposed methodology is composed of three modules: (1) additional data selection and realization; (2) characterization of additional data impacts, and (3) the welfare and socioeconomic analysis.

For the second module, the approach of Leeworthy et al. (2005) was used to estimate the population recreational visit behavior which is utilized in a modified utility model suggested by Train (1998).

For the welfare analysis; this work introduced an early application of preference calibrated benefit transfer method based on the work of Smith et al. (2000) and Smith, Van Houtven, and Pattanayak (2002) to assess the WTP for improved data collection to reduce uncertainty.

This interdisciplinary work contributed to the current understanding of benefit-cost assessment relevant to water quality mitigation through the introduction of socioeconomic attributes. The proposed methodology is practical and use publically available data collected by state and federal agencies across the US.

In Module 2, the state-of- the-art forecasting tool consisting RVM was used to estimate *ex ante* value of information. The transition from the predicted environmental impact (Module 2) to WTP estimation (Module 3) was achieved through developing visitation, utility, and benefits transfer models calibrated for the target population.

Module 3 clearly shows the major contribution of this work to the field of water quality mitigation through the development of WTP analysis. In Module 3, the socioeconomic value of information level is estimated using visitation, recreational utility, and benefit transfer models applied using Monte Carlo sampling to represent population variability.

Table 7. Summary of management application with two information collection scenarios for the Fishtrap Creek Catchment

Variable	Scenario 1	Scenario 2	Comments
Additional Data Realization			
Sampling Interval (δt), days	60	10	
Future number of samples/year	8	37	
Characterization of Additional Data Impacts			
Undetected TP loading, kg/year (Figure 18)	2,428.8	667.7	Frequent sampling corresponds to high detection of TP loading
Socioeconomic Estimates			
Median number of visits/year	11	11	Less base level information has higher utility with the potential to detect higher P loadings and a gain in utility of 0.12
Expected median utility	0.26	0.14	
Households' WTP ($/yr) at base level			
Minimum	57.7	42.2	On average, households are willing to pay extra $15/yr or 20% more to reduce uncertainty from 60 to 10 days sampling interval so that undetected TP loadings can be reduced by 1,761 kg/yr
Mean	98.0	83.3	
Maximum	183.7	170.0	
Standard Deviation	26.5	26.5	

The proposed methodology illustrated the capacity to derive multi-point estimates of WTP for a new setting using existing benefit estimates and the preference calibrated benefit transfer method.

The combined application of forecasting method using RVM, econometric models (visitation and utility), and benefit transfer technique to predict WTP estimation is a novel contribution to the NPS management literature. The proposed methodology provides future predictions for a single-period (on annual basis) that are transferable to a new environmental and population setting. The required data are typically accessible through public sources such as public domain socioeconomic databases on age and income; thus permitting its application on different environmental problems.

The methodology has the advantage of allowing stakeholders to allocate risk-reduction expenditures based on explicit WTP estimates specific for the target population. The success of this methodology is contingent on the quality of data. Even though the theoretical framework is well established; data quality and the lack of standard approaches to evaluate vital parameters such as utility level and calibration of transfer model parameters are limitations, but also provide directions for future research.

CHAPTER VI

SOCIAL WELFARE ANALYSIS OF DISTRIBUTIVE EQUITY IN NPS POLLUTION USING BENEFIT TRANSFER APPROACH

Successful pollution abatement policies in watershed management require a collaborative and long-term commitment from several contributing sources. In this context, social acceptability of considered policies evolves as a major factor to determine the potential success of these policies and poses a challenge to decision makers due its strong reliance on behavioral and social factors. Distributive equity emerges as a practical indicator of social acceptability of abatement policies in air and water quality applications. A common practice in cost sharing problems is to consider efficiency (least-cost) approach which normally ignores distributive equity.

In the context of watershed management; a theoretical framework for evaluating the tradeoff between efficiency and equity is developed. The recent literature provides a framework to determine equitable allocations of responsibility only at the high level of decision making (basin and watersheds level) and lacks the structural capacity to estimate impacts of the considered policies on the affected population (farmers). In this work, a novel theoretical framework is developed to elicit welfare measures of equity at the individual level (farmer). The new framework has the capacity to transform the equity related allocations at the watershed level to the individual (farmer) level and then estimate individuals' utility and WTP measures which is the contribution of this work to watershed management. A practical application of the new framework is provided using phosphorus loading reduction in the Fishtrap Creek Watershed in the Nooksack River Basin in northwestern Washington State.

Introduction and Background

Agricultural pollution is responsible for 60% of impaired river areas (US EPA, 2002). While pollutants from point sources (e.g. wastewater discharges) are easy to track and control; Non-Point Sources (NPS) are difficult to measure and manage (i.e. runoff from agricultural fields) (Sharply et al., 2001).

Today, significant controls are exerted on Point Sources through regulations such as clean water act; and there exists less control of NPS agricultural pollution loading (Johansson, 2002). The ecological risks posed by NPS are substantially more serious than those posed by pollution from point sources (US EPA, 2003, 2004). Nonpoint source pollution remains the major source of water pollution, accounting for approximately 70% of total suspended solids and 80% of the total phosphorus input.

The current practice of NPS pollution mitigation utilizes a range of measures related to the farming practices; from practical operational measures known as Best Management Practices (BMPs) to more radical measures such as land or crop retirement (Ribaudo, Horan, and Smith, 1999). For NPS pollution management, the allocation of pollution mitigation responsibilities amongst suspected sources is challenging due to the inherited uncertainty associated with identifying contribution of each source to the total load.

Environmental economics provide two major types of economic instruments to achieve NPS pollution loading reduction: (1) command and control instruments, and (2) economic instruments, both direct and indirect (Shortle and Horan, 2001). Command and control instruments are technology-based programs, where regulators identify and mandate mitigation strategies for each type of sources, e.g., the Total Maximum Daily Load (TMDL) program. As for the economic instruments, they are flexible and they allow group of polluters to choose their appropriate mitigation levels by using economic incentives to reach target reduction goal. An example of direct economic incentives is the tradable permits and taxes on ambient pollution levels. The indirect economic instruments involve taxing production inputs such as fertilizers or animal feed consumption in order to reduce the use of that particular input, hence reducing nutrients loads.

The command and control instruments are increasingly applied in the US. However, they are criticized for ignoring fairness and equity issues in allocating mitigation responsibilities among heterogeneous sources (Khadam and Kaluarachchi, 2006b). Economists argue that for a policy to be sustainable it has to recognize both efficiency and equity concerns. By “efficiency” economists refer to “Kaldor-Hicks efficiency.” which implies that those whom it benefits compensate those whom it harms fully (Adler, 2006). To achieve equitable solutions; extensive data collection is needed to monitor producers practices and loadings which accumulates high costs to decision maker. Moreover, the economic instruments which are designed to produce socially acceptable solutions are hurdled by the requirement of continuous and extensive monitoring across all polluters to facilitate information flow to help pollution exchange decision making (Shortle and Horan, 2001).

Today, the NPS pollution management by command and control policies such as TMDL is widely adopted across the US. For instance, by the year 1996 about 13,000 TMDL plans have been set and approved across the US (US EPA, 2004). The TMDL application includes explicit and implicit costs incurred by farmers and other stakeholders to reduce pollutants loadings. Explicit expenses include expenditures by farmers to control pollution (i.e., retiring crops and installing buffer strips). Implicit expenditures include opportunity costs which is the income forgone when pollution control practices are adopted. TMDL policy focuses on management practices and their water quality improvement without considering its welfare impacts which is a major limitation (Maguire, 2003). As more agricultural watersheds are managed by the TMDL process; issues of efficiency, equity, and uncertainty continue to hinder TMDL implementation. Since equity explicitly affects TMDL policy efficiency; the two variables need to be addressed concurrently (Keplinger, 2003).

Equity in NPS pollution management

Application of the TMDL policy has important implications on public welfare. One major limitation of TMDL policy is the disregard of issues of justice and equity in responsibility allocation (Maguire, 2003; Khadam and Kaluarachchi, 2006b). A sustainable TMDL policy has to be economically feasible and socially acceptable by involved parties (Spurlock and Clifton, 1982). The allocation of abatement cost amongst contributing sources in a TMDL policy is a major challenge because observed pollution may be generated beyond the boundaries of local watershed and it tends to span across political boundaries. Thus, the allocation of pollution control responsibilities has to address both economic efficiency and individual concerns of social justice (Bauch and Spahr, 1998). Typically, an efficient solution assigns different costs of pollution control for different sources such that the marginal abatement costs across all sources are equalized. To achieve equitable responsibility allocation; decision makers are challenged by: (1) uncertainties arising from hydrological variability and from the contribution of each source, (2) effect of multiple pollutants, and (3) derivation of abetment cost function that estimates the costs incurred by sources for given reductions (Khadam and Kaluarachchi, 2006b).

Numerous literature addressed some form of equity in a range of environmental management and health risk applications (Adler, 2006; Chavas, 1994; Levy, Chemerynski, and Tuchmann, 2006). In the context of cost sharing policies; social equity can be measured in terms of distributive equity (Johnson, Rutstrom, and George, 2006; Levy, Chemerynski, and Tuchmann, 2006). Equity and justice assessment are well established in the air quality management literature. For instance, Bovenberg and Goulder (2001) analyzed the equity in allocation of green house gases emission allowances by estimating the financial impact on companies and the potential to improve general equilibrium efficiency through reducing emission taxes.

In relation to water pollution, Spurlock and Clifton (1982) recognize the benefit of allocating different shares of pollution reduction burden among polluters to enhance abatement policy acceptance. Stephenson and Shabman (2001) recognize the need to represent heterogeneity in pollution reduction costs and suggested that reduction allocations should be determined for each watershed individually. Polluters in each watershed are then allowed to negotiate to reach a least cost allocation of pollution control responsibilities. Stephenson and Shabman (2001) argue that this approach will motivate collaborative solutions in addition to achieving a least cost solution to control pollution. The collaboration principle is the underlying concept of the several economic incentive approaches such as trading permits.

In a related work, Onal et al. (1998) represented distributive equity in their watershed management model. Authors maximized the aggregate economic returns at the watershed level through a range of agricultural practices including crop rotations and technology choices considering equity goals. Distributive equity is represented as a constraint that imposes a minimum diversification of economic losses across all farms. Recently, Khadam and Kaluarachchi (2006b) developed a theoretical framework for evaluating the tradeoff between economic efficiency and equity using several equity criteria. Authors developed efficiency-equity curves that quantify the cost of achieving known equity levels. However, the related works of Onal et al. (1998) and Khadam and Kaluarachchi (2006b) did not address welfare measures of equity. Also, the majority of the cost sharing research in watershed management has focused on the stakeholder level which is hardly applicable to the small scale of individual (i.e. farmer) level (Lubell, 2004).

Equity and benefit transfer approach

Economic literature provides several methods to evaluate non-market amenities such as social equity. Valuation methods are classified into revealed preference, where valuations are inferred from actual observations of choice behavior, and stated preference, where the valuations are directly obtained from hypothetical statements of choice. The revealed preference methods include Hedonic Pricing and Travel Cost Methods. As for the stated preference methods, people are presented with a hypothetical scenario and then asked to state explicitly what its worth to them. Economic valuation using direct approach (i.e. contingent valuation method) is the “first-best” strategy to collect the needed information. The stated preference methods are deemed to be more accurate for conducting benefit-cost analysis for environmental resources (Loomis, 1996). However, most stated preference studies are expensive and frequently unfeasible. When the stated preference methods are not practical; the Benefit Transfer Approach (BTA) emerges as a “second-best” option to evaluate equity of cost sharing policy. Even though the reliability of BTA is debatable; it remains attractive compared to the stated preference methods because it does not require expensive and lengthy data collection (Desvousges et al., 1992; Brouwer, 2000). The BTA for non market amenities evaluation is becoming increasingly popular for a wide range of environmental applications (Bergstrom and De Civita, 1999). The BTA requires derivation of a benefit transfer function that allows adjustment of previous estimates for a new setting (Loomis, 1996).

In this work, a theoretically sound behavioral model that consists of a derived WTP formulation based on assumed utility structure is developed. The behavioral model uses benefit estimates and related parameters to populate the model using previous equity studies (Pattanayak, Smith, and Van Houtven, 2004). The theoretical basis of WTP for quality improvement entails that the WTP is a function of pre-equity and post-equity policies.

The objective of this research is to enhance the present social acceptability assessment framework by including welfare measures of equity in cost sharing between members (i.e. TMDL). In this work, a practical multi-disciplinary framework is developed to estimate population welfare to achieve equity in the context of NPS pollution reduction responsibilities. The developed framework produces estimates of utility and willingness-to-pay (WTP) for distributive equity using BTA to produce new estimates using previous related studies. The suggested framework is applied to the Fishtrap Creek watershed in the Nooksack River Basin in northern Washington State.

The suggested framework addresses the tradeoff between economic efficiency and equity in allocation of pollution abetment responsibilities within the TMDL framework. For a given equity level, the suggested methodology produces several useful end points such as allocations of cost sharing between contributing land uses at the watershed level, and utility and willingness to pay estimates at the individual (farm) level.

Methodology

The analysis framework is structured of the following modules: (1) Equity level realization, (2) Equity level impact assessment, and (3) Equity welfare analysis.

The premise of the equity levels realization module (Module 1) is to represent equity levels in the context of watershed management in sensible measure to the stakeholders. A key task of Module 1 is to develop a watershed economic model that facilitates the minimization of the cost of a given pollution reduction at the watershed level with explicit equity levels. The watershed economic model determines the cost sharing scheme that corresponds to highest efficiency (minimum cost) at a given equity level. The anticipated outcome of the watershed economic model is the allocation of economic loss burden amongst contributing members (land use types). The premise of the equity impact assessment module (Module 2) is to transform the cost sharing scheme at the watershed level in a sensible measure at the individual (i.e. farmer) level. With equity policy a change in farm income (gain or loss) is expected. The anticipated outcome of Module 2 is the change in farmer income due to considering given equity level. In equity welfare module (Module 3), utility and WTP formulations that consider equity are derived. The economic analysis suggested in Module 3 represents the contribution of this work to the TMDL management literature. In this work, concepts and models developed in other works in the literature are utilized. For the watershed economic model, we use the economic model developed by Khadam and Kaluarachchi (2006b), which represents equity in abatement cost allocation in watershed management.

To assess the equity utility and WTP; we adopt the procedure described in Corneo and Fong (2006) to derive functional forms of the utility and WTP measures. Authors implemented a BTA to estimate WTP for distributive equity in the context of income loss due to tax allocation.

Module 1: Realization of equity levels scenarios

Watershed economic model. A watershed economic model is developed to estimate optimal cost sharing scheme at given equity levels. The watershed economic model hereafter referred to as the economic model allocates pollution reduction loads based on land uses in a watershed. Due to data availability limitations and to maintain the analysis transferability, equity is considered at the level of common land uses in a watershed. The assumption behind grouping pollution sources as land use types implies that enforcement of pollution reduction targets can be achieved through market-based economic incentives using collaborative approach (Khadam and Kaluarachchi, 2006b; Romstad, 2003).

A pollutant transport model is needed to estimate pollution production and transport from watershed as a function of land uses. Pollutant transport is estimated using specific land use erosion-scaled export coefficient that relates land uses to pollutant loadings considering sedimentation. The advantage of using erosion scaled export coefficient model is to include hydrologic variability impacts which produce more accurate estimates of pollutant loadings (Khadam and Kaluarchchi, 2006b).

For a watershed with j land uses (j=1,..,n) the generated pollution at the watershed outlet (L) is defined as

$$L=\Phi\times\sum_{j=1}^{n} A_j\times I_j\times K_j\times\left(1-M_j\right) \tag{18}$$

where Φ = annual sediment discharge as a function of annual runoff from watershed; Aj = area occupied by land use j (ha) in the watershed; Ij = pollutant input from land use j (Kg/ha) in the watershed; Kj = is erosion-scaled export coefficient for land use j in a watershed; Mj = level of management efforts (percent reduction in economic production); and n is the number of land uses.

Also, an economic model is needed to estimate economic losses and gains determined by pollution abatement policy for potential sources (i.e. land uses). The mutual use of watershed pollution loading and economic models allow estimating the allocation of pollutant reduction cost amongst sources to achieve stakeholder goals based on both equity and efficiency.

The watershed economic production is determined for each land use on the basis of per unit area outcome. The watershed economic production (η) is defined as follows:

$$\eta = \sum_{j=1}^{n} w_j \times A_j \tag{19}$$

where w_j = economic production of land use j in a watershed ($/ha).

Pollution abatement cost function. The quantification of the economic costs of pollution reduction is a vital component of this analysis. The availability of economic data related to costs of reducing pollution from different sources represents a persistent challenge for pollution reduction studies. Incomplete knowledge about the efficiency and cost of management options produces inefficient solutions. Previous literature show several approaches to obtain information related to abatement cost functions. For instance, Shortle et al. (1999) used direct questionnaires to elicit estimates of pollutants reduction cost from polluters. Another approach adopted by Elofsson, (2003) involves the estimation of the opportunity cost due to change in policy.

Alternatively, a continuous cost abatement function is adopted by Johansson and Randall (2003), Ancev et al. (2006), and Khadam and Kaluarachchi (2006b) where a single continuous function is assumed to describe the relationship between management costs and abatement effort for each pollution source. The advantage of this approach is to simplify the analysis by evading the need to estimate separate cost functions for each management option for each source. With a continuous function, a single cost function for each source (i.e. land use) is sufficient. Johansson and Randall (2003) developed phosphorus abatement cost function that relates reduction in phosphorus loads to the associated costs for each watershed in their study using quadratic abatement cost function. Recently, Khadam and Kaluarachchi (2006b) modified the abatement cost function suggested by Johansson and Randall (2003) to represent sources with variable function curvatures which is suitable for different sources or land uses. The cost function suggested by Khadam and Kaluarachchi (2006b) uses the percent reduction in economic production (M) instead of the absolute amount of pollution reduction and replaces quadratic cost function with a power function to allow representing the curvature of the cost function with different sources (land uses).

In this work, we focus on the application of the cost function. However, a detailed description of the abatement cost function is provided in Johansson and Randall (2003) and Khadam and Kaluarachchi (2006b). The general abatement cost function developed by Khadam and Kaluarachchi (2006b) is defined as follows:

$$C(M)=a\times M^{b} \tag{20}$$

where C is the cost of pollution loading reduction as a function of management cost; M is the percent reduction in economic production due to management effort or hereafter referred to as management cost; and a and b are coefficients.

The watershed cost of pollution management (χ) based on Equation 20 is defined in terms of farm land uses as follows:

$$\chi = C(M) = \sum_{j=1}^{n} \alpha_j \times M_j^{\beta_j} \tag{21}$$

where α_j = coefficient (\$), and β_j = coefficient (dimensionless)

Therefore, the watershed net economic production (π) after pollution loading is reduced is defined as

$$\pi = \eta - \chi = \sum_{j=1}^{n} w_j \times A_j - \sum_{j=1}^{n} \alpha_j \times M_j^{\beta_j} \tag{22}$$

<u>Distributive equity consideration</u>. Equity definition is determined by the unit of decision-making. In this study, equity is defined in terms of the distribution of management cost between land uses as a constraint for the optimization problem. Equity in management cost allocation (M) is considered between different land uses within the watershed. The consideration of equity at the watershed level represents a natural hydrological boundary and selecting land use is practical and convenient from an economic and management point of view. In this analysis, we define equity as equal distribution of ratio of economic losses to total economic production (Khadam and Kaluarachchi, 2006b).

The Equity Measure (EM) is defined as the variation in percentage of relative pollution costs (χ) to production across land uses (η) and it is formalized as follows:

$$EM = 1 - \frac{\sum_{j=1}^{n} \left| \frac{\chi_j}{\eta_j} - \frac{\chi_T}{\eta_T} \right|}{n \times \chi_T / \eta_T} \tag{23}$$

where n is the number of land uses j; and the subscript T refers to the total land uses in the watershed ($T = \sum n$).

To account for stochastic nature of runoff, Chebyshev's inequality is used similar to Khadam and Kaluarachchi (2006b) as follows:

$$E\left[L\right]+\delta\times\mathrm{var}[L]^{0.5}\leq L_{\max} \tag{24}$$

where μ is best estimate sediment loading (long term) defined as $\mu=E\left[\Phi\right]$, δ

is the confidence level at probability (ρ) is defined as $\delta=(1/1-\rho)^{0.5}$, and σ^2

is the variation of observed Φ from the μ defined as $\sigma^2=\mathrm{E}\left[(\Phi\text{-}\mu)\right]$.

The EM considers distributive equity at the watershed level between land uses. Therefore, equity can be represented as a constraint in the watershed economic production maximization problem as shown in Equation 25.

$$\mathrm{Max}:\overline{Z}=\left(\sum_{j=1}^{n}\mathrm{w}_j\times\mathrm{A}_j-\sum_{j=1}^{n}\alpha_j\times\mathrm{M}_j^{\beta_j}\right) \tag{25}$$

Subject to:

$$1-\frac{\sum_{j=1}^{n}\left|\frac{\chi_j}{\eta_j}-\frac{\chi_T}{\eta_T}\right|}{n\times\chi_T/\eta_T}\geq\mathrm{EM}_{\min} \tag{25a}$$

and

$$\mathrm{L}_{\max}\geq\mu\times\sum_{j=1}^{n}\mathrm{A}_j\times\mathrm{I}_j\times\mathrm{K}_j\times(1-\mathrm{M}_j)+\delta\times\left[\sigma_s\times\left(\sum_{j=1}^{n}\mathrm{A}_j\times\mathrm{I}_j\times\mathrm{K}_j\times(1-\mathrm{M}_j)\right)\right]^{0.5} \tag{25b}$$

where $\mathrm{EM}_{\min}$ is the minimum equity to be satisfied.

Practically, Equation 25 is solved at desired level of equity EM_{min} in order to find an equitable-efficient solution and it provides a simple and attractive procedure to characterize this equity –efficiency tradeoff which is the focus of this work.

The described watershed economic model minimizes management cost at desired equity levels. Therefore, the watershed economic model produces efficient solution with known equity level. The anticipated outcome of the watershed economic model is the allocation of management costs between (M_j) among land uses j that satisfies maximum efficiency at desired equity level.

Module 2: Equity levels impact assessment

The goal of Module 2 is to express equity policy at the watershed level (using land uses) in a suitable measure for welfare analysis which is the individual (farmer) level. An underlying assumption is needed to facilitate the transition from a large scale equity policy to the small scale of farmers' level. The farmer income is viewed as a combination of the related land uses. The transition from large to small scale requires several economic data at various levels. At the land use level, economic production and management cost data are provided in the economic model developed earlier in Module 1. At the farm level; the fraction of each land use per farm is obtained from agricultural census data of the considered watershed.

To identify equity impacts, the change in income due to equitable policy compared to a non-equity policy is considered. For each land use, the management cost (M) determined by non-equitable allocation is compared with M related to equitable allocation with known equity. The equity policy at the watershed level categorizes land uses based on their pollution loading and economic production to two types: (1) Receiver and (2) Giver. The Receiver land use is the one that is assigned less M with equity policy than with no equity policy. The Giver land use is the one that is assigned more M with equity policy than with no equity policy. The emerged classification of land uses similarly separates farmers to two classes. With equity policy, farmers enjoy increase in income or incur economic loss based on the contribution of Giver and Receiver land uses to the total farm income. To formalize the equity policy impact on income; the net income for farmer (i) with no equity policy ($y'_{ef}(i)$) is defined in terms of the management cost determined by non-equity policy for land use j (M_j^{ef}) as follows:

$$y'_{ef}(i)=y(i) -\sum_{j=1}^{n}\left[f_j(i)\times M_j^{ef}(i)\right] \tag{26}$$

where $y(i)$ is the farm income with no management cost (zero pollution reduction), $f_j(i)$ is the fraction of total area of land use j in the watershed for farmer i.

Similarly, with equity policy the farmers' net income is defined by

$$y'_{eq}(i)=y(i) -\sum_{j=1}^{n}\left[f_j(i)\times M_j^{eq}(i)\right] \tag{27}$$

Therefore the impact of equity on farmer i is defined as

$$\Delta y_{eq}(i)=y'_{eq}(i)/y'_{ef}(i) \tag{28}$$

Based on the fraction of each land use in a given farm; farmers can be classified to Receiver and Giver with equity policy. Formally, a Receiver farmer is the one with positive change in income, and a Giver farmer is the one with negative change in income due to equity. The anticipated outcome of this analysis is monetary estimates of the change in income related to equity for each farm.

Module 3: Equity welfare analysis

The goal of Module 3 is to develop welfare measures of the equity policy simulated in Module 1 and represented in Module 2 as change in income at the individual (farmer) level. The developed welfare measures represent a novel contribution to the social acceptability assessment framework in watershed management. The theoretical economic constructs derived by Corneo and Fong (2006) provide a transferable and practical approach to estimate utility based WTP formulation for equity in various policies that affect income distribution between members. It is beyond the scope of this study to repeat the theoretical basis of the BTA which is described in the original work of Corneo and Fong (2006). Instead, we concentrate on the derivation of WTP formulation, proposed modifications, and the practical aspects of WTP estimation. In this analysis, a WTP formulation that integrates individual perception related to equity in cost sharing policy such as TMDL is developed.

A basic utility function is needed to derive the farmers' WTP equation.

The equity utility function developed by Corneo and Fong (2006) is modified for this work's purpose. The original utility model considers equity and its effect on individual consumption (C). In this study, the consumption (C) is substituted by the change in income due to equity $\Delta y_{eq}(i)$ which indirectly indicates consumption. Individuals derive utility from two factors: 1) the consumption of goods using the modified income by equity and 2) the satisfaction knowing that certain equity is achieved in the community. The functional form of farmers' equity utility function is defined as

$$u_{ie}=u(\Delta y_{eq},h_i)=\omega\times\Delta y_{eq}+\theta\times(1\text{-}2h_i) \tag{29}$$

where $h_i = 0$ if farmer i is a Receiver and $h_i = 1$ if farmer i is a Giver, ω and θ are weighting non-negative scalars.

The first term of Equation 29 conveys the impact of income change and the second term represents the individual response to social equity. The second term of Equation 29 represents individual response where the coefficient θ has a constant value for all individuals and the dummy variable (h_i) has a value of 0 or 1, therefore, the individual response to equity is not sensitive to individual variability which is unrealistic for the purposes of this work.

Corneo and Fong (2006) defined the coefficient θ as follows:

$$\theta=(1+\gamma)\psi \tag{30}$$

where ψ is a constant and γ represents individual preferences.

To incorporate individual variability, the coefficient θ is re-defined to represent equity valuation that reflects individuals' heterogeneity. In Equation 30; we define γ as the relative position of individual i with respect to average population in terms of the change in income due to equity ($\Delta y_{eq}(i) \big/ \overline{\Delta y}_{eq}$). The constant ψ is defined as policy equity level (e) which ranges from 0 to 100 %. Therefore, the modified coefficient θ that represents farmer i variability (θ_i) is defined as

$$\theta_i = \left(1 + \Delta y_{eq}(i) \Big/ \overline{\Delta y}_{eq} \right) e \tag{31}$$

Another important feature of Equation 29 is that it represents the two states of farmer as a Receiver and Giver. A Receiver farmer is expected to obtain positive utility due to gain in income and a Giver farmer is expected to incur a negative utility due loss in income. The two types of farmers' are represented in Equation 29 in the ratio $\Delta y_{eq}(i)$ and the dummy variable h_i. The ratio $\Delta y_{eq}(i)$ increases as the farmer is allocated economic gain (higher residual income with equity than with no equity). Similarly, the ratio $\Delta y_{eq}(i)$ decreases as the farmer is allocated economic loss (less residual income with equity than with no equity). The dummy variable (h_i) represents farmers' vote for the equity policy (accept) or against equity (reject). Therefore, a receiver farmer would have a $\Delta y_{eq}(i)>1$ and $h_i = 0$ which produces utility value larger than 1. Similarly, a giver farmer would have $\Delta y_{eq}(i)<1$ and $h_i = 1$ which produces negative utility values.

The next step in the welfare analysis is to estimate the farmers' WTP to avoid or to apply a given equity policy. The theoretical basis of WTP entails that the WTP is a function of pre-policy (i.e. no equity) and post-policy (i.e. equity) levels (Mitchell and Carson, 1989; Smith et al., 2000).

WTP Formulation- In this analysis; a preference calibrated model is employed to construct an accurate benefit transfer model for a new setting using reported estimates from previous studies. The modified utility function is used to derive WTP function. A probit model embedded in a random utility framework (RUM) is considered to develop

WTP formulation for equity. The probit model based on Corneo and Fong (2006) is given as

$$\Pr[d=1 | y'_{eq}, h_i] = \Pr\left[\omega(z-ty'_{eq}) + \theta(2-4h_i) + \varepsilon > 0 \,\middle|\, y'_{eq}, h_i\right] \tag{32}$$

where d is a dummy variable which equals 1 with equitable policy, t is empirical constant defined as marginal tax rate and ε is error term.

The RUM model is modified in this work to incorporates measures of farmer response to equity policies (accept or reject) due to farmers' type as a Receiver or a Giver.

The modified RUM model substitutes θ defined in Equation 30 with θ_i defined in Equation 31. Therefore, individual variability is represented explicitly in Equation 32 and produces Equation 33.

$$\Pr[d=1 | y'_{eq}, h_i] = \Pr\left[\omega(z-ty'_{eq}) + e(2-4h_i) + e(2-4h_i) \times \left(\frac{\Delta y_{eq}(i)}{\overline{\Delta y}_{eq}}\right) + \varepsilon > 0 \,\middle|\, y'_{eq}, h_i\right] \tag{33}$$

The modified RUM model in Equation 33 can be solved as a binary probit model as described in Corneo and Fong (2006). The WTP for farmer (i) for additional equity can be estimated similar to Corneo and Fong (2006) as follows:

$$\mathrm{WTP}(i) = t \times \theta_i / 2\omega \tag{34}$$

Management Application

An outline of the suggested framework application procedure is shown in Figure 25. The suggested framework is intended to provide a practical and transferable approach to estimate welfare value of equity in allocation of pollution control responsibilities at the watershed level with multiple land uses.

A realistic case study is considered to demonstrate the applicability of the suggested framework in practical setting. The developed methodology is applied to Fishtrap Creek watershed to provide insight into considering equity in phosphorus NPS pollution abatement.

Study area description

The Water Resources Inventory Area (WRIA) 1 is located in the northwest corner of Washington State. The Nooksack River Basin is located in Whatcom County in WRIA 1 covering an area of 825 square miles and encompassing a diverse geography ranging from the Cascade Mountains in the northwest to the lowlands and discharging to Bellingham Bay (Almasri and Kaluarachchi, 2004).

The lowlands area is the focus of collaborative efforts by local and state official parties to improve water quality (Hood, 2000).

Earlier studies on Nooksack River Basin indicate that agriculture, dairy farming, and waste lagoons contribute the most to the observed elevated pollutants levels (i.e. nitrogen, phosphorus, and coliforms) in the Noocksack River Basin (Carey, 2002).

Fishtrap Creek Watershed. Fishtrap Creek Watershed shown in Figure 26 is a representative watershed of the lower Nooksack River Basin. Fishtrap Creek is a small agricultural dominated watershed (95 km^2). The Fishtrap Creek watershed provides habitat for a variety of fish species and it is identified as a major source of bacterial, nitrate, and phosphorus (P) loading. Fishtrap Creek Watershed is characterized by intensive agricultural and dairy production. Major sources of P in the Fishtrap Creek Watershed are agriculture fertilizers, animal manure, and atmospheric deposition.

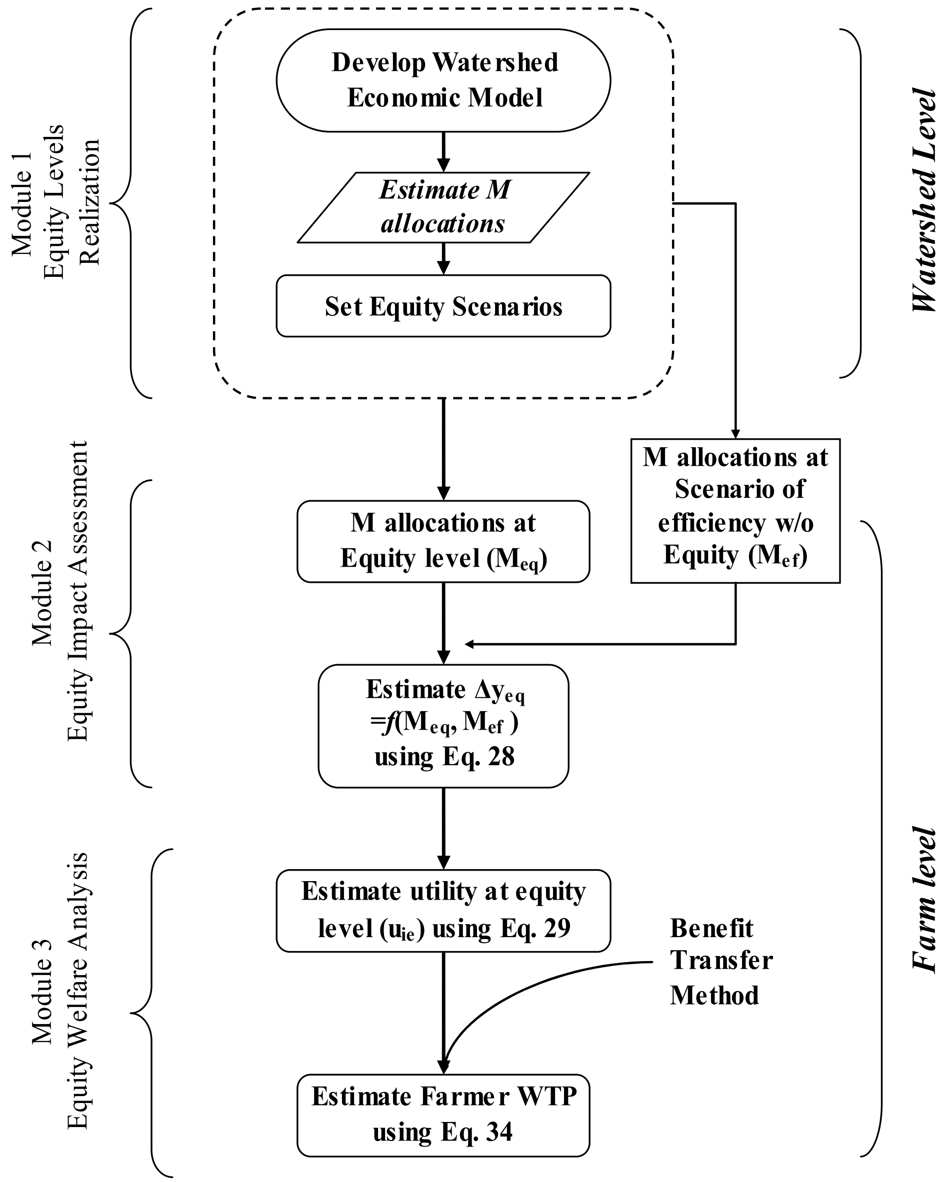

Figure 25. Schematic of the suggested framework featuring the three modules.

The NPS loadings in Fishtrap Creek are mainly attributed to fertilizer application and manure storage. The urban pollution loadings from the cities of Abbotsford and Lynden are diverted to streams other than the Fishtrap Creek; therefore, the contribution of urban loadings is limited.

In Table 8 we summarize the areas and P-application rates of each land use type. The major land use class by area is agriculture, followed by urban land use. However, the most influential land use to P inputs is dairies followed by agriculture.

The observed Total Phosphorus (TP) concentration in Fishtrap Creek frequently exceeded the US EPA limit of 0.1 mg/L (Khadam and Kaluarachchi, 2006a).

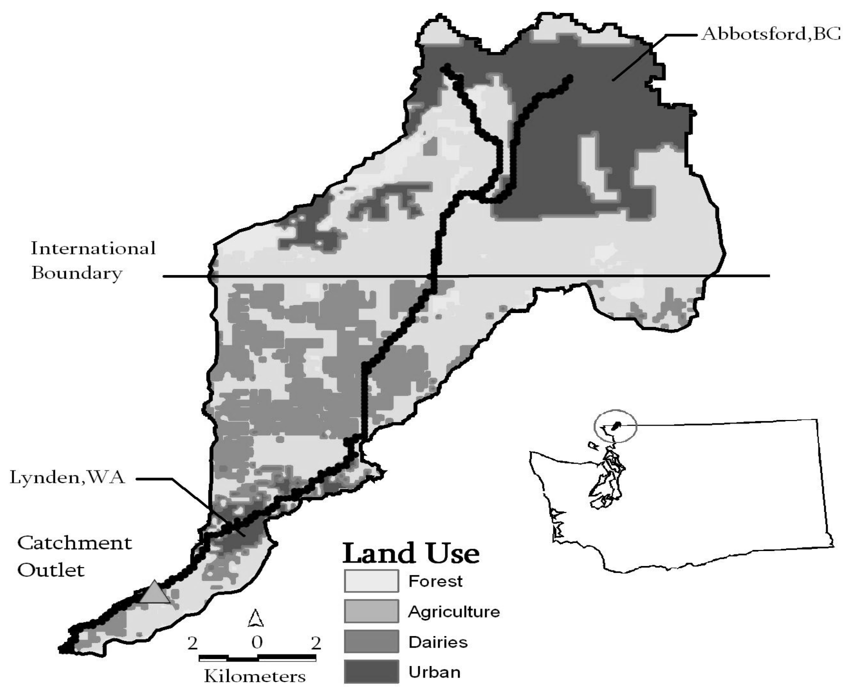

Figure 26. The layout of Fishtrap Creek Watershed showing land-use types.

Table 8. Summery of major economic variables and the abatement cost function parameters used in the optimization model estimated for Fishtrap Creek Watershed

Land use	**Area (ha)**	**w[a] \$/yr/ha**	**H[b] \$/yr**	**Abatement cost function** A^c **x** 10^6 **\$**
Agriculture	4896	6,400	31,052,800	31.05
Dairy	1381	13,500	18,738,000	18.74

a. Calculated Economic Production for land use
b. Long term annual sediment loading
c. Coefficient for abatement cost function for each land use

Therefore, we focus on TP loadings as a proxy of NPS pollution loading in Fishtrap Creek Watershed.

In the Nooksack River basin, protection of fish habitats and recreational fishing are major challenges for stakeholders (Joy, 2000). Therefore, reducing NPS pollutants loading have positive effect on the welfare of local population. A comprehensive review of the state of water quality management in the Fishtrap Creek Watershed is provided in Almasri and Kaluarachchi (2004) and Khadam and Kaluarachchi (2006a).

Scenario description

The framework practicality is shown best by application to realistic case study. The stakeholder wishes to implement an abatement policy to reduce phosphorus NPS loading from Fishtrap creek watershed in the Nooksack River Basin. The present state of Fishtrap creek watershed indicates an annual P application of 232,906 kg and 145,560 kg for dairies and agriculture respectively, which produces P loading at the watershed outlet of approximately 5000 kg per year. The stakeholder whishes to reduce loadings at the watershed outlet by 1000 kg per year using a policy with distributive equity of 50% and 100% compared to a no-equity TMDL policy. This scenario is simulated using the suggested framework and demonstrated through the next discussion.

Module 1: Equity levels realization. The tasks of module 1 include developing economic and P-loading models that recognizes distributive equity in produced cost sharing allocations amongst sources. A main task of the economic model is to develop watershed specific abatement cost function.

The economic analysis is considered at the land use level. Data requirement for the watershed economic model include P application rates for agriculture and dairy land uses, calibrated abatement cost function for each land use, crops and dairies production and prices data. Economic production data are obtained from Washington State's annual agriculture and animal production statistics (Washington Agricultural Statistics Service, 2003).

The calculated estimates of related parameters needed to estimate economic production as a function for each land use are summarized in Table 8.

The P loading model requires water quality data including erosion-scaled export coefficients (K) and sediment discharge (Φ) information for Fishtrap Creek Watershed which is provided in Khadam and Kaluarachchi (2006a).

The needed parameters for estimating P loading as a function of land use are summarized in Table 9. The cost function for phosphorus loading reduction is developed for each land by calibrating Equation 21. In order to calibrate cost function for each land use; a minimum of three empirical data points is needed. The considered calibration points and approach are similar to Khadam and Kaluarachchi (2006a). Therefore, calculated coefficients for the cost functions for land uses are similar to Khadam and Kaluarachchi (2006a) and summarized in Table 9.

The economic model described from Equation 18 to Equation 25 is solved using Linear Programming optimization (LP) at desired pollution reduction increment with minimum equity level. Estimates of management cost M for agriculture and dairy land uses related to equity level are produced and equity-efficiency tradeoff analysis is provided in the results discussion.

Module 2: Equity level impact assessment. For Fishtrap Creek Watershed; information about fractions of dairy and agricultural land uses at farm level are obtained from GIS databases and the Washington State's annual agriculture and animal production statistics (Washington Agricultural Statistics Service, 2003). The farming community in Fishtrap Creek Watershed is found to have one type farming activity in general. The majority of the farmers practice single activity such as dairy or agricultural production with insignificant mixing of the two activities.

Table 9. Summary of land use areas, erosion export and phosphorus application for Fishtrap Creek Watershed. Source: Khadam and Kaluarachchi, (2006a)

Land use	**Area (ha)**	**P loading rate (kg/ha)**	**K[1] (Kg^{-1})**	**Φ[2] Kg/yr**	**TP loading (kg)**
Agriculture	4896	30	5.64×10^{-9}	3,088,500	151,739
Dairy	1381	167.8	4.57×10^{-9}		23,1668

1. Erosion scaled export coefficient developed in Khadam and Kaluarachchi (2006a).
2. Long-term annual average sediment loading

The farming community in Fishtrap creek watershed includes 27 dairies and 22 agriculture production farms. The known farm areas with the calculated economic production and management costs for land uses (provided in Module 1) are used to estimate the change in income due to equity using the Equations from 26 to 28.

The maximum income with out abatement cost (y(i)) is calculated. Then using the sum management costs (M); the residual income is calculated using Equation 26 for non-equity policy and using Equation 27 for equity policy. Then, equity impact which is the output of Module 2 is calculated using Equation 28 and used as input in Module 3.

Module 3: Equity welfare analysis. In this work, we illustrate the application aspect of estimating utility and WTP for a new setting. An elaborate description of the related parameters estimation is provided in Corneo and Fong (2006).

The farmer WTP for additional equity is estimated using Equation 34. In practice, the coefficient ω is determined empirically using related previous studies. Similar to Corneo and Fong (2006), a diverse sample of US households is considered to estimate the coefficient ω. Authors recovered the calibrated parameter ω by fitting the theoretical model described from Equations 29 to 34 using a survey of 5000 US households and an estimate of -0.066 for ω is used. The parameter t is determined empirically from Saez (2004) and others and it is estimated for the US population at 25.56%.

To estimate the coefficient θ_i, the equity impact at the individual level ($\Delta y_{eq}(i) \big/ \overline{\Delta y}_{eq}$) is utilized in Equation 31 which produces individual specific values. Ultimately, an individual (farmer) specific estimate of WTP is estimated using Equation 34.

Results and discussion

Equity and efficiency tradeoff. A major output of the economic model is the tradeoff between efficiency and equity. The tradeoff between efficiency and equity is best illustrated graphically. The Pareto front for equity and efficiency are shown for three abatement levels as shown in Figure 27. The tradeoff plot in Figure 27 show important patterns. For instance, with higher pollution reduction increments, maximum possible efficiency is reduced at given equity level. Also, for a given M level (i.e. 3000 kg reduction); Figure 27 indicates that efficiency is negatively correlated with equity which is in agreement with Khadam and Kaluarachchi (2006b).

Next, the performance of the abatement cost function is shown in Figure 28. The positive impact of using exponential cost function is shown in the exponential increase in abatement cost at increasing P-reduction increments.

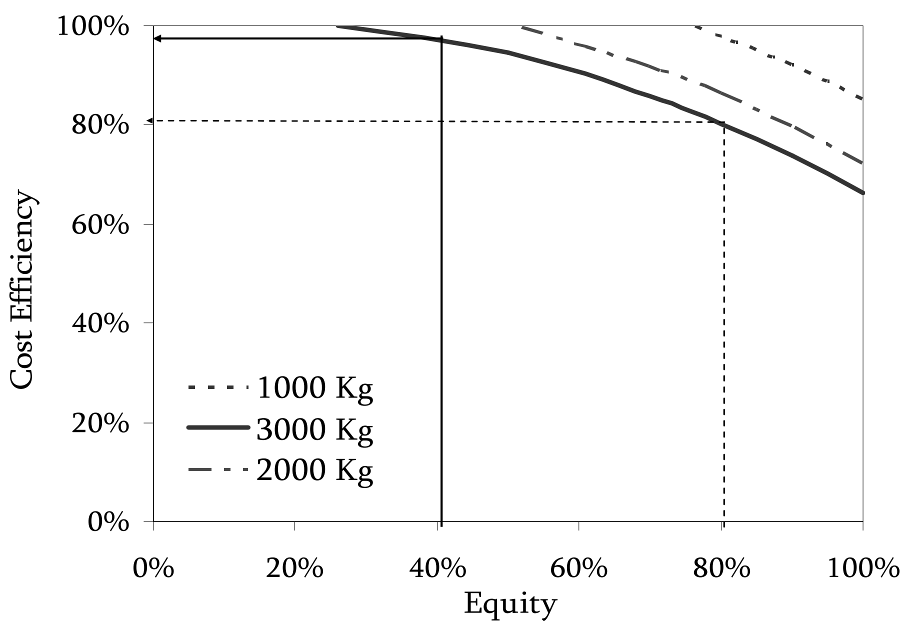

Figure 27. Efficiency-Equity tradeoff plot at the watershed level for Fishtrap Creek Watershed. Source: Khadam and Kaluarachchi (2006b).

Also, for a given P-reduction increment, abatement cost (M) increases with equity which is consistent with the observed pattern in Khadam and Kaluarachchi (2006a) and Ancev et al. (2006).

Equitable allocation produces higher pollution costs than the inequitable efficient allocation. For instance, with 1000 kg reduction (from 5000 to 4000 loadings), abatement cost rises from \$20 million (point X) to \$27 million (point X') at zero and 100 percent equity, respectively.

Next, we analyze the efficient solution for Fishtrap Creek Watershed over a range of increasing equity levels.

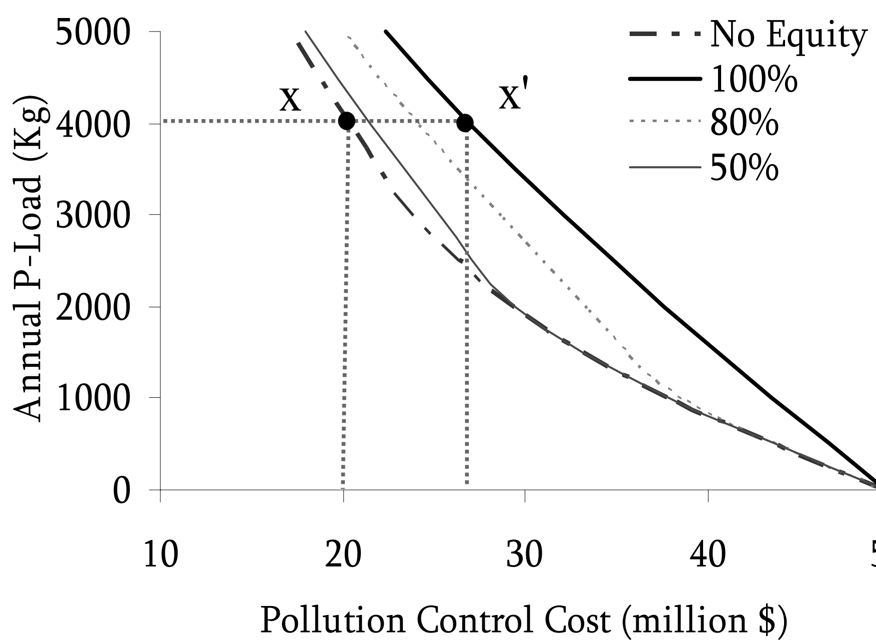

Figure 28. Abatement Cost Function for a range of P loading Levels for Fishtrap Creek Watershed at different equity levels. Source: Khadam and Kaluarachchi (2006b).

Equity policy re-distributes economic loss allocations between land uses and accordingly between farmers which produces the two types of farmers the Giver and the Receiver.

Equity impact on allocation between Receiver and Giver sources is presented in Figure 29 for the two reduction levels 1000 and 3000 (P kg /yr) in the watershed.

The incurred costs for agriculture and dairy land uses to achieve efficient reduction goal are used to estimate equity policy impacts; therefore, the change in income due to equity is shown graphically in Figure 30. For instance; at low equity levels (0 to 20%); the Receiver source (dairy) is assigned highest M with no equity distribution and as equity increases, the assigned M decreases.

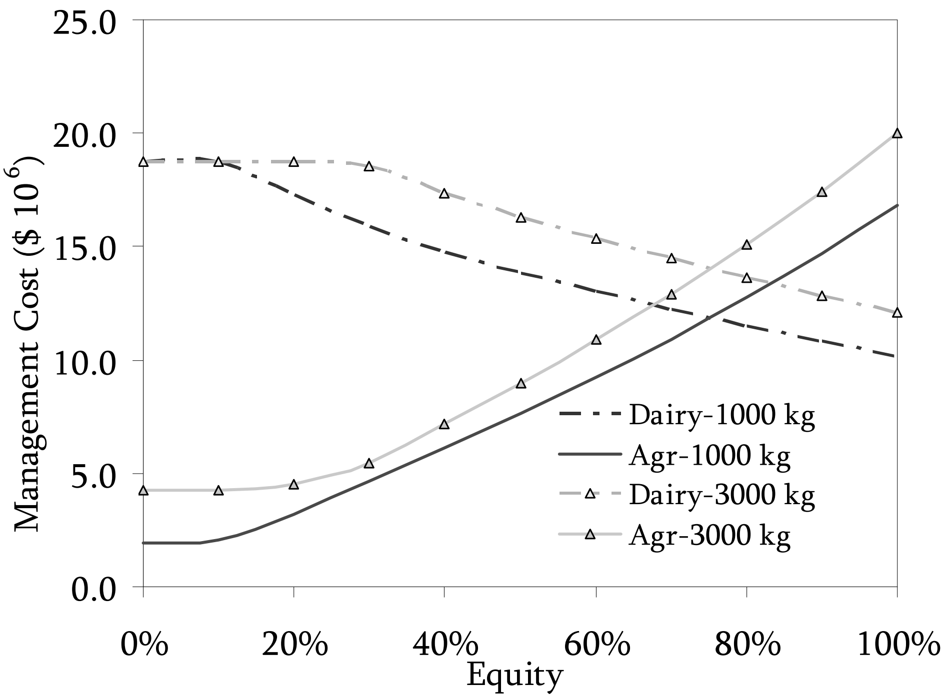

Figure 29. Economic loss as management cost (M) for the common land uses in Fishtrap creek watershed at increasing equity levels.

On the other side, the Giver source (agriculture) is assigned low M at low equity levels (0 to 20%) and as equity level increases the assigned M increases accordingly. This pattern is anticipated due to the high difference in P loading between dairies and agriculture as indicated in Table 8.

In this work, the change in farmers' income related to equity is used as input in welfare analysis. The approach to calculate the change in income is best illustrated in Figure 30. Equity in pollution reduction allocation has a positive impact on dairies income (Δy_d) due to the reduction in allocated M from point d to point. d' On the other side, equity has a negative impact on agriculture income (Δy_a) due to the increase in allocated M from point a to point a'.

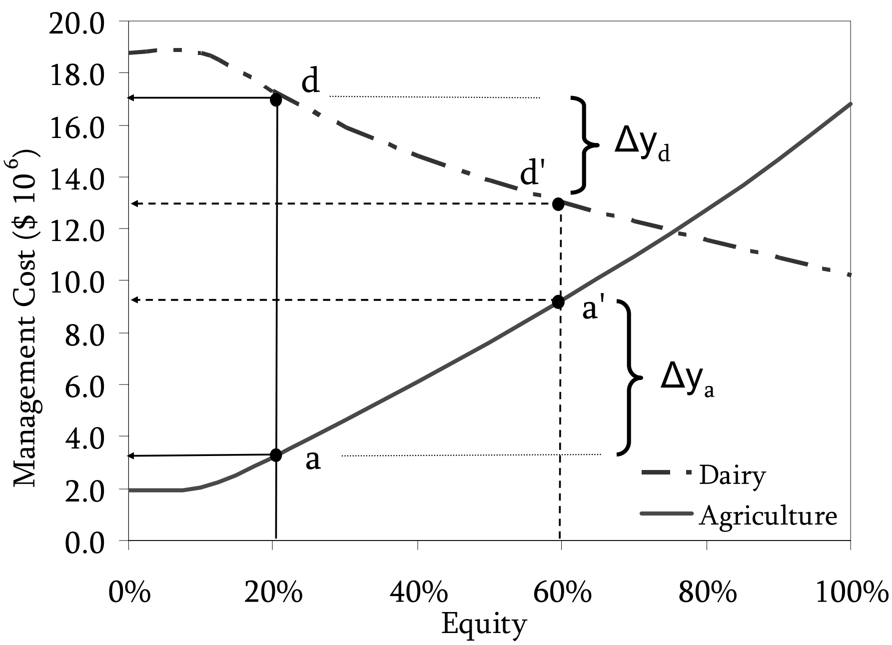

Figure 30. Schematic of economic loss and gain estimation as a function of equity levels for considered land uses for the scenario of 1000 kg reduction in annual P loading. The plot features the Giver and Receiver land uses.

<u>Equity utility and WTP</u>. The redistribution of M allocations between land uses due to equity policy reflects directly on farmers. The farmers of Fishtrap Creek Watershed are directly affected by equity. The change in farmers' utility due to considering the described scenario is presented in Figure 31. The equity policy produced both positive and negative utility changes for the Receiver (dairy farmers) and Giver (agriculture farmers) respectively. The equity utility indicates a linear relation with change in income and farm size. The increase in equity from 50 to 100 percent translates to more M re-allocation from the Giver to the Receiver which causes higher impact on utility change.

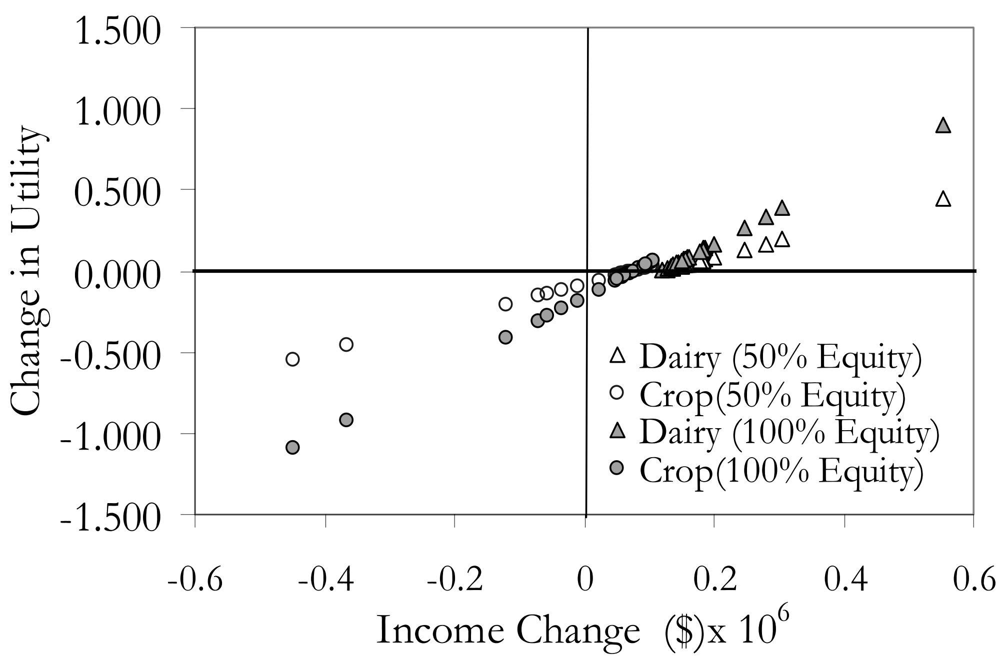

Figure 31. The change in utility as a function of the change in income change due to the two levels of equity 50% and 100% using efficient policy with no equity as a reference. The simulated scenario is 1000 kg/yr P loading reduction.

Next the impact of equity policy on farmers' WTP is shown in Figure 32. The WTP is presented as a function of farm area which is a proxy for farm income.

As the farm area and income increases; the intensity of income change, utility, and therefore the WTP becomes significant as equity increases. The positive and negative signs represent the farmer response to equity policy impact (accept or reject). Dairy farmers represent the Receiver; therefore they have a WTP to increase equity. Similarly, agriculture farmers represent the Giver; therefore, they indicate WTP to avoid having equity policy implemented.

<u>Calculation example</u>. A detailed calculation of the framework application using the scenario of 1000 kg P loading reduction at 50% equity compared to zero equity is elaborated in Table 10.

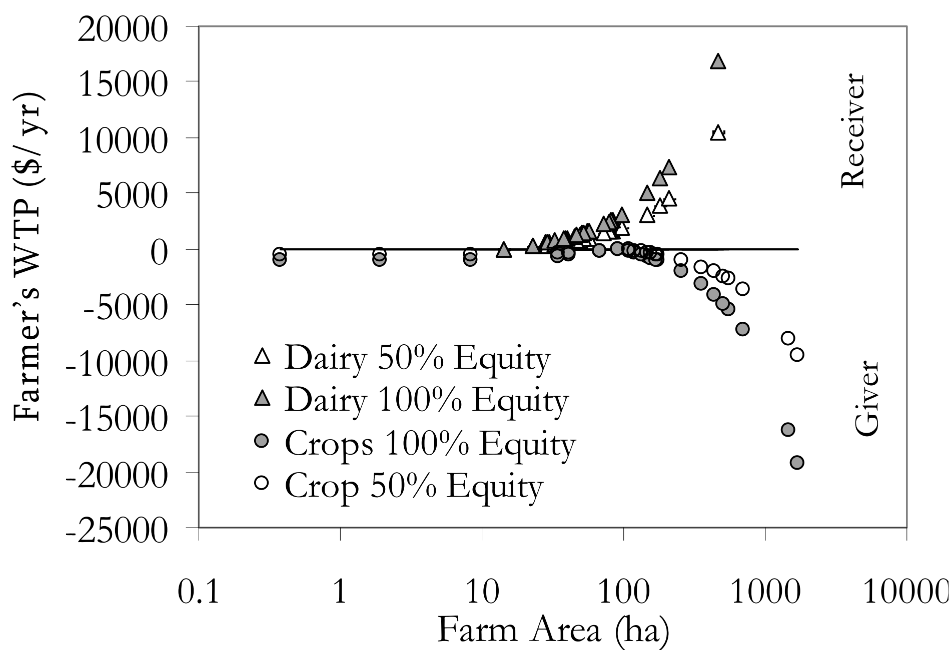

Figure 32. Farmers' WTP as a function of Farm Size in Fishtrap Creek Watershed for the P-loading reduction level of 1000 kg/yr at 50% and 100% Equity levels.

The calculation begins with the economic model (in Module 1) which produces allocations of M determined by efficient solution prior equity (A) and post equity (B). The equity impact is explicitly shown in the change in M allocations for land uses prior and post equity. For instance, at efficient solution with no equity dairies farming will be suspended due to their high P loadings (allocated 100% reduction in income), while at efficient solution with 50% equity, dairies farming are allowed to operate with 82% reduction in income.

Therefore, dairies are classified as Receivers because equity has positive effect on their economy. On the other side, agricultural farming are assigned an income reduction of 40% prior to equity, while with 50% equity they have to incur higher income reduction at 63% which is 23% higher due to equity. Therefore, agricultural farmers are classified as Givers because equity has a negative effect on their economy.

Next, the change of income (Δy_{eq}) due to 50% equity is calculated per unit area of land use (in Module 2) as a gain of 2297 ($/ha-yr) for the Receiver and a loss of 766 ($/ha-yr) for the Giver. To transfer the analysis from the general policy level (land uses) to the practical level (farmers); data of the fraction of dairy and agricultural land uses for each farm are developed. As described earlier, farmers in Fishtrap creek watershed have one type activity either dairies or agriculture.

Using known farms profile information such as area of each farm, type of land uses, and estimates of Δy_{eq} for land uses; the change in income at the farm is quantified for the dairy and agriculture farms.

Table 10. Summary of the framework application to incorporate 50% equity in TMDL policy to reduce 1000 kg of P loading for Fishtrap creek watershed

Variable	**Efficient Policy with no equity (A)**		**Efficient Policy with 50% equity (B)**		**Comments**
Land Use	**Dairy**	**Agriculture**	**Dairy**	**Agriculture**	
Module 1: Equity level Realization					
Management Cost (M) in \$/yr	18,738,030 (100%)	2,038,855 (40.34%)	13,845,419 (82.77%)	7,648,251 (62.68%)	Allocation at maximum efficiency with given equity level
Module 2: Equity impact Assessment (from A to B)					
Identify farmer type			Receiver	Giver	
Δy_{eq} for land use in \$/ha-yr			+2297	-766	Based on income gain or loss due to equity
Δy_{eq} for farms in \$/yr Mean & (Std. deviation)			27 farms +181,208 (205,144)	22 farms -252,927 (347,185)	
Module 3: Socioeconomic Estimates of Equity					
Equity Utility from 0 to 1 (from A to B)					
Mean & (standard deviation)			0.066 (0.091)	-0.0808 (0.152)	
Farmers' WTP (\$/yr) at base level (from A to B)					
Minimum			13.571	-9625	At watershed level, farmers community have a positive WTP at \$5684/yr to obtain 50% equity
Maximum			10,540.46	-5	
Mean			1535.74	-1626	
Standard Deviation			2100.37	2552	
Aggregate Farmers WTP			41,465	-35,781	

The equity positive impact on dairies is calculated as an average gain in income of \$181,208 (\$/yr) for 27 farms and the negative impact on agriculture farms is calculated as income loss of \$252,927 (\$/yr) for 22 farms. The high variability in income loss and gain is related to the wide range of farm sizes.

Next, the calculated scaled utility at the farm level (in Module 3) indicates a utility gain for dairies at a mean of 0.066 and a utility loss for agriculture at a mean of -0.08 for the described scenario. The high variability in utility function is expected due to the wide range of Δy_{eq} due to the linear type utility function which preserves the high variability in the farm size and income.

Finally, the WTP is calculated at the farm level. The dairy farmers have annual WTP mean and standard deviation of 1535 and 2100 (\$/yr), respectively, for 50% equity. For agriculture farms; the mean and standard deviation are -1420 and 2552, respectively, for 50% equity. The large standard deviation values indicate high variability in farm size (area and income).

The positive WTP estimates for dairy farmers are anticipated because they are the beneficiary party of the equity policy. Similarly, agriculture farmers' indicate negative WTP because they are the liable party of the equity policy. The large standard deviation with respect to mean is an in indicative of the high variability observed in input variables such as Δy_{eq} and utility.

The use of BTA in equity consideration of watershed management is relatively new. Thus, the validation of WTP estimates against comparable estimates from previous studies in the literature is not possible. However, if the observed trends of produced end points such as the equity-efficiency tradeoff, the utility, and the WTP are consistent with similar studies and expected social behavior, then the confidence in the analysis output validity increases. Our WTP estimates fall within the reported range of Corneo and Fong (2006) WTP estimates for equity in income tax distribution at an average of $ 14,350/household-yr.

Summary and Conclusion

This work is intended to aid the long time debate of considering social impact of regulatory policies where distributional equity and justice arise as central issue for contributing individuals and stakeholders. We investigate the social preferences of individuals facing a regulatory policy with negative externality (income loss). The goal of this work is to extend the present equity benefit-cost analysis methodology to integrate socioeconomic measures to achieve desired equity level in a regulatory policy.

The suggested methodology elicits societal benefit of a decision of integrating a known distributive equity as a measure of social justice.

The proposed methodology was demonstrated in the context of NPS pollution abatement by applying a TMDL regulatory policy in Fishtrap Creek Watershed in the Nooksack River Basin. We estimated the impact of distributive equity in a TMDL policy application. The three modules of the proposed methodology consist of: (1) Equity levels realization; (2) Characterization of equity levels impacts, and (3) Welfare measures of equity. The initial two modules adopted the watershed economic model developed by Khadam and Kaluarachchi (2006a). In the third module, a practical socioeconomic framework that introduces social equity concepts is developed.

The equity welfare analysis developed in Module 3 represents the contribution of this work to the benefit-cost approach used in TMDL management. However, the utilized concepts are based on the work of Corneo and Fong (2006) for estimating WTP for equity in the context of income tax allocation. The welfare analysis evaluated the WTP using the change in utility. The analysis found that the change in income due to equity have a considerable impact on individuals' utility and WTP. The utility and WTP estimates showed a robust change (increase or decrease) for large farms which is consistent with expected individual behavior.

A major practical advantage of the proposed methodology is that it provides an alternative to traditional data intensive WTP and welfare measures. The proposed methodology extends beyond putting together disparate estimates of Fairness and justice from different valuation methods; instead, the method utilizes these estimates along with a "theoretically sound" structure to produce transferable and adaptable estimates to different scenarios.

The success of this methodology depends on the quality of data and the availability of similar studies for the purposes of populating the model parameters and validation of results. At this point, scarcity of similar studies prohibits such validation. However, validity can be evaluated by contrasting the observed trends of related variables with similar works in different applications. Although the theoretical framework is well established in social applications, the lack of a standard approach to evaluate vital parameters such as the utility function scalars (ω and θ) is a major limitation but also provide directions for future research. However, the proposed methodology remains attractive because it quantifies societal value of equity impacts in monetary terms which is valuable to decision making. Also, it requires data from sources that are generally accessible such as agricultural census databases.

CHAPTER VII

SUMMARY, CONCLUSIONS, AND RECOMMENDATIONS

The objective of this dissertation is to develop a watershed management framework that integrates societal value of related decisions. Chapters IV to VI present the body of the work and the main scientific results of this dissertation. The research is structured into three sections, dealing with contaminated groundwater, surface water pollution, and social acceptability of pollution reduction regulations. This chapter summarizes the major tasks, conclusions of the work, and recommendations for future research.

Summary and Conclusions

In this research, the general framework descried in Chapter III is used to develop and apply practical framework for common applications in water resources management. The conclusions obtained are presented for each application.

Application 1: Decisions in groundwater monitoring management

The goal of this application is to investigate the socioeconomic value of additional information to reduce uncertainty in the context of contaminated groundwater management. The general framework is applied to reducing uncertainty in risk assessment due to the exposure to contaminated drinking water from a point-source carcinogen. For the first and second modules, we adopt the approach and theoretical case study suggested in Maxwell et al. (1998) and Maxwell and Kastenberg (1999). The general framework was modified and fitted for assessing the levels of information on subsurface heterogeneity represented by several hydraulic conductivity correlation scales.

The last module is the welfare analysis which is based on the work of Pattanayak, Smith, and Van Houtven (2004) and it is revised here to address incremental risk reduction and society's WTP in environmental management.

The developed framework allows ex ante evaluation of additional information impacts, in which the health risks attributed to alternative additional information scenarios on subsurface heterogeneity are quantified. In this methodology, mortality risk is the outcome of a structured range of discrete values of health risk produced by discrete increments of additional data representing subsurface heterogeneity. Levels of heterogeneity are simulated by generating several random hydraulic conductivity fields correspond to preset several correlation scales using the turning bands method (Tompson, Ababou, and Gelhar, 1989) which is a common geostatistics tool.

The welfare analysis produces estimates of utility gain attributed to health risk reduction as a result of better information collection scenarios. Then using the BTM, a transfer function is calibrated for the target population to elicit population WTP for incremental additions in information.

The main conclusions for application 1 are summarized in the next discussion. The JUV analysis indicates that the variability in population (largely due to age) has a higher impact on WTP than uncertainty due to subsurface heterogeneity. This application used an expanded range of variability of individual health exposure parameters similar to other health risk studies (Maxwell et al., 1998; Zhao and Kaluarachchi, 2002) and therefore explains the considerable impact of population variability on the WTP. We investigated the utility function and found that age and the change in health state due to mortality risk (expected illness hours) have a considerable impact on individuals' utility. For WTP, we found that age and initial health state have a robust impact on the WTP. The utility and WTP estimates showed a robust decline for old age groups (>50years) which indicates that the age-dependent health state has a strong impact on welfare measures.

The proposed methodology is limited to predictions of a single-period which in this case is on annual basis. However, the methodology has the advantage of allowing a manager to allocate risk-reduction expenditures based on explicit WTP estimates.

The proposed methodology is attractive because it requires data from sources that are generally accessible, for example, public domain socioeconomic databases on age, income, health statistics, etc., thus permitting its application on different environmental problems.

Application 2: Decisions in surface water quality protection

NPS pollutant loadings from a watershed are controlled by highly uncertain processes that need to be properly described to help decision-making. Seasonal (temporal) variability is a well-known challenge in surface water quality management (Ouyang et al., 2006). In this problem, levels of information in the temporal dimension are developed and simulated.

For Module 1 of the general framework, we developed scenarios of different information levels represented as several secondary data sets reflecting different sampling frequencies. The sampling frequency levels correspond to different uncertainty levels in phosphorus NPS loadings due to hydrologic variability. As the sampling frequency increases; the level of uncertainty decreases. The case study is the Fishtrap Creek Watershed in the Nooksack River Basin in Washington State. An intensive water quality data set from 1987 to 1995 is the primary data set used to build secondary data sets. A series of secondary water quality data sets are sampled from the primary data set for the same period at a set of sampling intervals (ranging from 1 day to 120 days) which produces a set of time series data at increasing sampling interval. The produced data sets are used as input for the next analysis.

For Module 2, the goal is to express the impact of information levels in usable measures for the welfare assessment of the target population. In this case, estimated undetected future annual TP loadings are used as the impact of information levels.

To estimate the undetected future TP loadings, we utilize the RVM forecasting model (Tipping, 2001) to predict P loadings for a future period. The secondary data sets prepared earlier in Module 1 are used in the training and testing phases of the RVM. The model uses precipitation and runoff as inputs and will produce the TP loadings as output. Then, the trained model is used to predict the TP loadings for a desired period. The discrepancy between the actual and the predicted TP loadings provides a measure of the level of information. A rising pattern in the undetected loadings is observed at longer sampling periods or low frequency sampling programs. The increasing error in TP loading estimates motivates decision-makers to select a sampling program with a higher frequency but at a higher cost too. The estimated undetected TP loadings are used as input for welfare analysis.

For Module 3, we investigate the economic value of information for reducing uncertainty in TP loading forecasts. The welfare analysis concepts employed here are based on the work of Pattanayak, Smith, and Van Houtven (2004). The economic analysis considers a population with known characteristics in several aspects including income, household size, age, education level, and the number of visits to recreational areas. The population characteristics data are collected from various sources including the latest US Census (for year 2000) and national surveys on recreation and Environment (Leeworthy et al., 2005). Thereafter, age dependent probabilistic distributions are prepared and utilized in a Monte Carlo simulation to produce the simulated population. A utility function is developed to represent the improved protection of environmental resource due to additional information into consumer preference settings. For this application, the environmental resource is fish habitats and the dependent recreational uses for the local population (Joy, 2000). The NPS phosphorus loadings have negative effects on recreational activities of the local population.

In the welfare analysis, we estimated the target population's WTP to obtain higher utility due to reducing risk of undetected loadings to a given water body as a result of a potential decision to collect more frequent samplings. For the welfare analysis, we will utilize the BTM to calibrate the WTP benefit transfer function to improve water quality for recreational uses especially fishing. The WTP analysis utilizes a vector of household attributes namely income, costs of fishing trips, WTP estimates from similar studies to calibrate the benefit transfer model parameters for the target population.

The main conclusions for application 2 are summarized in the next discussion.

Both of information collection level and population variability has a robust impact on utility change and WTP estimates. The individuals' expected utility gain and WTP decrease as the baseline information collection level increases indicating a pattern of decreasing marginal benefit of additional information which is consistent with findings of Smith, Van Houtven, and Pattanayak (2002). Individual variability is largely dependent on age as the related social variables such as household income and visitation frequency are determined by age groups. Therefore, age have the highest impact utility and WTP estimates. At older age groups, the expected gain in utility and WTP decrease due to the reduction in visitation frequency for old age groups which is consistent with findings of Dalton et al. (1998). To sustain framework practicality and transferability; the considered pollution welfare impacts are limited to the protection of recreational fishing resources aspect of water bodies which excludes other important non-market values such as bequest value. However, the methodology has the advantage of helping stakeholder to select surface water quality monitoring expenditure that reduces pollution risk to acceptable level for a given population. The described application have high potential to be applied to new setting due to its manageable data requirements and due to the flexibility of using RVM model for forecasting loadings for any desired period.

Application 3: Decisions to integrate social equity in NPS pollution management

In this application, a framework to assess societal benefits of improving equity in economic loss distribution regulation is developed and applied to a pollution reduction regulation or TMDL policy in the case of watershed management.

The framework is applied on the farming community of Fishtrap Creek Watershed in the Nooksack River Basin in Washington State. In Module 1, for a given pollution reduction increment minimum cost solutions are calculated with different equity levels and the related distributions of economic loss amongst farming activity types are defined at the general policy level. In Module 2, produced economic loss distributions are used to determine farmers' economic losses using fine scale economic data obtained from agricultural census databases at each equity level. Then, for a known equity increment determined by adopting equitable distribution of economic losses compared to a non-equitable one; the change in income loss at the farm level is quantified. The change in economic loss shares causes some farmers to incur more income losses and others to enjoy less income loss with respect to the typical no-equity distribution. The change in income loss at the farmer level is used as input to equity welfare analysis.

In Module 3, a benefit transfer model was developed based on BTM suggested by Corneo and Fong (2006) to assess WTP for additional equity in income tax allocation.

In this application, we select to use distributional equity as a robust indicator of social acceptability in the context of change in income. However, we recognize that other equity criteria might be used based on the considered problem. The developed benefit transfer function uses coefficients calibrated for US population and considers annual time step.

This framework helps stakeholder to quantify aggregate and individual estimates of social benefit and cost of integrating social acceptability (distributional equity) in TMDL policy to achieve sustainable policies.

Recommendations

The dissertation attempts to contribute to the methodological development in environmental decision making by estimating decisions welfare impacts using benefit transfer method (BTM). Based on the concepts developed and the results demonstrated throughout the described applications, the following recommendations might be considered for future research.

Groundwater monitoring management

For this application, several aspects of developing the framework remain subjective. In light of lack of standard approach, it is recommended to compare other approaches cited in the literature. In this application, it is worthwhile to investigate model performance using different utility and WTP formulations.

The estimated WTP in this application is based on the benefit of reducing mortality health risk arising from exposure to one contaminant. In reality, a groundwater MN provides insights into a host of contaminants. We anticipate that if more contaminates are considered, the social benefit of reducing uncertainty (due to additional information) and WTP estimates would increase accordingly raising the upper limit of socially acceptable investment in monitoring.

For health risk exposure assessment, we represent individual variability by considering an expanded range of exposure factors as variables; however, the cancer slope factors were used as constants. For future work; we encourage the exploration of using variable slope factors linked to related social indicators such as health state.

Surface water quality protection

The success of this application is contingent on using a reliable and long-term water quality data set at a spatially valued location (watershed outlet) and on the comparability of the source studies used in benefit transfer to new setting. Therefore, a thoughtful selection process of these components is expected from analyst to produce defendable results.

Because future predictions are made using a regression model (RVM), all considerations to improve RVM performance apply here.

In this application, WTP estimation is limited to one non-market commodity that is the protection of recreational fishing resource in a water body against phosphorus NPS loadings. The framework is constructed to elicit the welfare impact of pollutant loading reduction which directly fits the decision making theme of this dissertation. However, to be practical, the degradation effects of loaded pollutant(s) should be considered instead.

Defining correlation between loadings and damages is sophisticated and often not feasible. Therefore, a research focusing on quantifying this correlation for common NPS pollutants and presenting this information to population is an asset to improve BTM performance. Similar to the first application; combining several NPS pollutants such as nitrates and coliforms increases the expected benefit and WTP to improving surface water sampling.

NPS pollution management
considering equity

In this application, a practical framework to assess distributional equity of economic loss as a measure of social acceptability of TMDL policy is developed.

Equity definition considers only economic impacts, while in reality, social acceptability is a comprehensive term that involves environmental justice considerations. In the context of NPS pollution, environmental justice refers to the distribution of environmental benefit. For future work, environmental justice needs to be considered and compared to economic losses to achieve sustainable allocation.

In this application, a continuous single function describing the relation between costs and abatement efforts for land use types are assumed. Although the cost function is theoretically sound, its derivation and validation requires several reliable empirical data on the cost of pollution control measures. Therefore, analyst is encouraged to derive cost function from several reliable data points.

<u>Benefit transfer method</u>

The concept of transferring benefits from previous studies arises in practical policy analysis when analysts do not have the luxury of implementing original CVM studies.

For each of the three described applications, a benefit transfer function is developed to adjust WTP estimates from source studies using related social characteristics. The benefit transfer function is a theoretically sound approach; however, it requires access to reliable studies on same or similar application for calibration and validation purposes. Some applications such as equity have limited number of studies investigating their economic value which restricts the pool of qualified studies from which to draw information. Therefore, collecting data on CVM studies in the form of accessible databases to researches is indispensable advancement towards regulating and encouraging further implementation of BTM in new environmental applications.

Inescapably, BTM introduces subjectivity and uncertainty by the assumptions considered to develop transfer function formulation. The key question is whether the added subjectivity and uncertainty surrounding the transfer is acceptable.
Therefore, there is a need to develop a standard approach to evaluate validity of benefit transfers. Research in this direction is a valuable investment towards improving confidence in BTM outcome.

Validation of BTM. At this point, literature suggests two types of validity checks: internal and external (temporal) checks.

The internal validity check refers to the quality of source study in terms of comparable purpose, sizable sample, and acceptable CVM approach. The external validity check refers to repeating a source CVM study after some time has elapsed since an initial and comparable study is conducted to evaluate stability of WTP estimates overtime.

For BTM application, stability suggests that the findings from older CVM studies can continue to be used to evaluate new applications.

Transfer error estimation. Ready et al. (2004) suggested using an absolute transfer error measure to estimate the error of benefit transfer. Using a simple absolute measure of error is an oversimplification of highly subjective application and introduces risk of incorrect appraisal about BTM outcome if based only on error quantity while the other validity checks are ignored. Therefore, depending on such one dimensional measures is not recommended.

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APPENDIX

RVM Model Calibration

RVM fitting performance for data collection scenarios represented by different sampling intervals. The parameters are bias, Mean Absolute Error (MAE), and Root Mean Square Error (RMSE), and Index of Agreement (IoA).

Samp. Int. (day)	Percent of data	Testing				Training			
		Bias	RMSE	MAE	IoA	Bias	RMSE	MAE	IoA
1	100.0	-0.2811	0.833531	0.64885	0.86708	1.21E-05	1.21E-05	1.2E-05	1
4	25.0	-0.13075	0.746123	0.54447	0.88668	-3E-11	2.96E-05	1E-05	1
6	16.7	-0.40776	0.891961	0.7031	0.8527	1.51E-12	1.1E-06	1.8E-07	1
8	12.5	-0.15384	0.837524	0.6019	0.86183	-3.5E-11	1.28E-05	3.6E-06	1
10	10.0	-0.27213	0.73731	0.56899	0.8898	2.19E-12	9.12E-07	4E-07	1
12	8.3	-0.03483	0.792206	0.5389	0.87503	3.01E-10	4.96E-05	1.7E-05	1
14	7.2	-0.14309	0.716601	0.52184	0.88599	-7.7E-09	0.000174	8.4E-05	1
16	6.3	-0.18249	0.75681	0.57865	0.88109	2.2E-10	3.98E-05	1.4E-05	1
18	5.5	-0.05487	0.751884	0.52005	0.87814	9.06E-11	3.66E-06	8.5E-07	1
20	5.0	0.37684	0.863791	0.57514	0.79302	-6.9E-09	4.39E-05	1.6E-05	1
22	4.6	0.06207	0.938622	0.68331	0.796	2.1E-09	0.000181	7.6E-05	1
24	4.2	-0.13751	0.847087	0.61175	0.86163	-3.2E-10	1E-05	5.6E-06	1
26	3.8	-0.43392	0.757316	0.64249	0.87984	2.77E-09	0.000319	0.00013	1
28	3.6	-0.07078	0.77848	0.56604	0.88494	-1.1E-08	0.000283	0.00013	1
30	3.3	0.09135	0.791983	0.61887	0.85598	-1.6E-08	0.000189	6.3E-05	1
32	3.1	0.13843	0.797139	0.65617	0.85037	9.73E-09	0.000181	7.5E-05	1
34	3.0	-0.0621	0.890696	0.7037	0.76386	-7.3E-08	0.000379	0.00018	1
36	2.8	0.29255	0.96874	0.64337	0.7016	-2.1E-08	0.001572	0.00088	1
38	2.6	-0.23061	0.797214	0.59242	0.8763	3.91E-14	2.52E-10	1.5E-10	1
40	2.5	0.57063	1.152099	0.76335	0.5594	-9E-11	3.18E-07	1.6E-07	1
42	2.4	-0.24795	0.778143	0.65542	0.85212	3.24E-09	1.52E-05	5.2E-06	1
44	2.3	0.07812	1.11494	0.80225	0.64328	1.81E-12	2.94E-08	1.6E-08	1
46	2.2	0.22762	0.754973	0.54628	0.84539	5.65E-07	0.002221	0.00114	1
48	2.1	0.22129	0.824651	0.6191	0.80891	1.56E-11	1.89E-07	7.4E-08	1
50	2.0	0.21507	0.772326	0.56293	0.79128	-2.4E-11	7.14E-07	3.2E-07	1
52	1.9	0.02357	0.873409	0.71015	0.82021	9.88E-07	0.003632	0.00229	1
54	1.8	0.30523	0.769319	0.55541	0.79946	-2.8E-10	2.37E-06	1.2E-06	1
58	1.7	0.04904	0.919952	0.74763	0.84216	8.07E-14	1.31E-09	7.1E-10	1
64	1.6	0.234	0.954676	0.79941	0.69497	1.01E-09	3.43E-05	2.2E-05	1
66	1.5	0.03856	0.746043	0.54913	0.83903	-3.8E-11	5.41E-07	2.1E-07	1
70	1.4	0.20135	0.676463	0.41962	0.80636	-8.9E-11	4.31E-07	2.4E-07	1
78	1.3	-0.05942	0.737182	0.6657	0.86111	-1.7E-15	3.46E-10	1.2E-10	1
84	1.2	0.04352	0.786798	0.58577	0.84704	-1.9E-11	3.29E-07	1.5E-07	1
92	1.1	0.14369	0.736997	0.58584	0.87786	4.89E-10	7.27E-06	4.1E-06	1
94	1.1	0.1891	0.812218	0.49556	0.84558	2.68E-12	5.98E-09	2.3E-09	1
100	1.0	-0.06011	0.825743	0.61318	0.82933	1.85E-07	0.0009	0.00051	1
108	0.9	-0.14843	0.485419	0.45448	0.92158	6.61E-11	7.74E-07	3.3E-07	1
110	0.9	-0.26654	0.391862	0.38028	0.93015	2.27E-06	0.005055	0.00325	0.99999
114	0.9	0.3237	0.836413	0.58296	0.82228	-6.2E-10	1.28E-06	5.7E-07	1
118	0.8	-0.04034	0.659117	0.57618	0.91706	8.21E-07	0.000466	0.00022	1

CURRICULUM VITAE

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EDUCATION

Ph.D., Civil and Environmental Engineering (Jan 2004- expected May 2008)
Utah State University, Logan, UT
Dissertation title: Decision analysis using social welfare measures in water applications

M.S., Irrigation Engineering (Jan 1999-May 2003)
Utah State University, Logan, UT
Thesis title: Nutrients and fecal coliform removal efficiency via free water surface constructed wetland for lagoon wastewater treatment effluent

B.S., Civil and Environmental Engineering (Oct 1990- Jan 1995)
The University of Jordan, Amman, Jordan

EMPLOYMENT HISTORY

- Research Assistant, Utah Water Research Laboratory, Logan, UT (Jan 04- current)
- Research Assistant, Utah Water Research Laboratory, Logan, UT(June00- Nov 02)
- Teaching Assistant, Civil and Environmental Engineering, Logan, UT (Feb 04 – Jan 06)
- Agricultural Engineer, Amman, Jordan (June 95 – Dec 99)

AREA OF EXPERTISE

- Developed an application to integrate social economic measures in a study on benefit cost analysis of uncertainty in subsurface heterogeneity.
- Developed an application to integrate social economic measures in a study on reducing error in NPS loading forecasting.
- Developed an application to integrate social economic measures in a study on estimation of social acceptability in NPS pollution reduction regulations.
- Groundwater contaminant and transport modeling:
    - MODFLOW, Visual MODFLOW, GMS.
    - Visual MODFLOW implementation for a study on the effect of uncertainty in hydrolic conductivity on health risk posed by contaminants

- Machine learning (data-driven models):
  - RVMs, SVMs, ANNs.
  - Used Relevance Vector Machines (RVM) in various applications including, pollution loading forecasting, and streamflow modeling.

- Optimization and model calibration techniques:
  - genetic algorithms, simulated annealing, and Shuffle Complex Evolution (SCE).

- Rainfall runoff modeling:
  - SAC-SMA, MIKE-SHE, TOPMODEL

- Multivariate statistics: numerous data mining, classification and regression techniques.

PUBLICATIONS

Journal Articles:
In Review:

- **Ashraf A. Shaqadan,** and Jagath Kalauarachchi (2008), Analysis of willingness-to-pay for uncertainty reduction in the management of contaminated groundwater.
- **Ashraf A. Shaqadan,** and Jagath Kalauarachchi (2008), Socioeconomic analysis to assess additional data collection strategies and corresponding willingness-to-pay in water quality mitigation.

Conference Papers:

- **Shaqadan, A.** and J.J. Kaluarachchi (2007). Benefit-cost analysis for groundwater remediation considering socioeconomic measures. *Proceedings of the Annual Conference of Environmental and Water Resources Institute*, Tampa, Florida, May.

Poster Presentations:

- **Ashraf A. Shaqadan**, Jagath Kalurachchi and Yasir H. Kaheil; Integration of socioeconomic measures in benefit-cost analysis for additional data collection in groundwater contamination. (AGU fall meeting 2006)

Oral Presentations:

- **Ashraf a. Shaqadan,** and Ryan Dupont; The use of surface constructed wetlands for lagoon wastewater treatment. (Spring runoff conference meeting, 2004).

CLASSES TEACHING (TEACHING ASSISSTANT)

- Groundwater Engineering
- Contaminant transport
- Engineering Hydrology

OTHER RELATED SKILLS

Software

- Operating Systems: Windows, UNIX, Linux, Mac
- Basic: Word, Excel, Access, Powerpoint
- Geographic Information System: ESRI ArcGIS (ArcInfo, ArcView – all versions, also including ArcHydro), ERDAS Imagine, Map Info.
- Programming Languages: C++, FORTRAN, VB, VBA, Visual Studio.Net 2003/2005
- Statistical and Mathematical Packages: R (CRAN); Matlab- including Matlab compiler, Simulink, S-Plus, Maple

Languages

- English *(Fluent)*
- Arabic *(Native)*

MEMBERSHIPS

- American Geophysical Union (AGU)- member
- Groundwater Scientists and Engineers (NGWA)-member

HONORS AND AWARDS

- Research Assistantship, Logan UT 2004 to present
- Research Assistantship, Logan UT 2000 to 2002