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Koel Ghosh

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The thesis of Koel Ghosh has been reviewed and approved* by the following:

James S. Shortle
Distinguished Professor of Agricultural and
Environmental Economics
Thesis Advisor
Chair of Committee

Ann N. P. Fisher
Professor of Agricultural and Environmental
Economics

Stephan J. Goetz
Professor of Agricultural and Regional
Economics

Stephen L. Rathbun
Associate Professor of Statistics

Stephen M. Smith
Professor of Agricultural and Regional
Economics
Head of the Department of Agricultural
Economics and Rural Sociology

* Signatures are on file with the Graduate School

ABSTRACT

This dissertation is a compilation of three essays in environmental economics on the related issues of economics of environmental investments under uncertainty, adaptation to climate change, and information in environmental management. The unifying theme across the three essays is various aspects and dimensions of environmental **decision-making under uncertainty**. Wherever relevant, an attempt has been made at incorporating an explicit spatial treatment of the research problems.

The first essay explores the issue of uncertainty and its implications for the design and timing of adaptation policies. The essay combines a literature review on the topic of uncertainty in environmental economics with a literature review of adaptation to climate change and synthesizes the findings to inform adaptation policy research under uncertainty. The optimal timing of investments in adaptation measure to climate change is part of effective policy design, but has been largely neglected in the literature. The presence of uncertainty, irreversibility, and adjustment costs that characterize adaptation problem complicates the analysis of optimal timing of adaptation measures. The essay examines how these and other elements impact timing decisions of adaptation measures and explores conditions under which earlier investment in adaptation is justified.

The second essay looks at the issue of ecosystem adaptation to climate change under uncertainty. The essay highlights the importance of including climate change as a possible stressor in ecosystem management, as climate change could potentially alter the spatial distribution of the habitat sites. The uncertainty surrounding climate change and

its impacts on habitat sites has important implications for optimality of investments in ecological projects. The essay uses the Submerged Aquatic Vegetation restoration program of the Chesapeake Bay as a case study to determine optimal investment decision-making in ecological restoration under climate change.

The third essay investigates the role of strategic information collection under uncertainty by examining the expected value of information in integrated sampling of the economy and the environment for nonpoint pollution management. In a first best world, environmental regulator sets different levels of the pollution control instrument for non-point polluters based on their productivity and pollution types, thereby minimizing the abatement costs of pollution. Information on the abatement costs of any pollution control policy is not available, oftentimes forcing regulators to select uniform control instruments. Uniform control instruments do not take into account the spatial heterogeneity across the landscape that creates differences in pollution and productivity types, and therefore do not minimize the abatement costs of pollution. Essay 3 tests and finds, in context of a Conestoga River watershed in Pennsylvania, that there is value of information in integrated sampling procedures of the environment and the economy. Information obtained from such integrated sampling procedures does help to create more efficient pollution control policies.

TABLE OF CONTENTS

LIST OF FIGURES viii

LIST OF TABLES ix

ACKNOWLEDGMENTS x

ESSAY 1: UNCERTAINTY AND CLIMATE CHANGE IMPLICATIONS FOR ADAPTATION POLICY AND TIMING 1

1.1 Introduction 1
1.2 Objectives and Methodology 5
1.3 Uncertainty in Environmental Economics 7
1.4 Brief Overview of Adaptation Literature 15
1.4.1 Adapt to What? 17
1.4.2 Who or what Adapts? – System Characteristics 18
1.4.3 How does Adaptation Occur? 22
1.4.4 Modification of ‘What to Adapt?’ 24
1.4.5 Costs and Benefits of Adaptation 25
1.4.6 Vulnerability Revisited 27
1.4.7 New Model for Adaptation Assessment 30
1.4.8 Uncertainty and Adaptation 35
1.5 Timing and Adaptation Measures 41
1.5.1 Uncertainty and Irreversibility 42
1.5.2 Catastrophic Events 44
1.5.3 Adjustment Costs 46
1.5.4 Risk Attitudes 48
1.5.5 Technology 48
1.5.6 Auxiliary Benefits 49
1.5.7 Direction of Influence of Key Elements Combined 49
1.6 Conclusion 51
1.7 References 53

ESSAY 2: OPTIMAL STRATEGIES FOR ECOLOGICAL RESTORATION UNDER CLIMATE CHANGE 59

2.1 Introduction 59
2.2 Climate Change and SAV Restoration Program 62
2.2.1 SAV Restoration Program in the Chesapeake Bay 62
2.2.2 Potential Impacts of Climate Change on the SAV Restoration Program 65
2.2.3 Case Study: Area and Decision Problem Under Climate Change 67
2.3 Objectives and Methodology 74

2.4 Model 75
2.5 Implementation of the Model 81
2.5.1 Restoration Methodology 81
2.5.2 Time Horizon 81
2.5.3 Calibration of the Model Parameters 82
2.5.3.1 Restoration Success Ratio 82
2.5.3.2 SAV Loss Rate 83
2.5.3.3 Wetlands Gain 84
2.5.3.4 Restoration Cost 86
2.5.3.5 Discounting 87
2.5.3.6 Benefit Function – Choice and Calibration 87
2.5.4 Data 88
2.6 Results 90
2.6.1 Baseline 90
2.6.2 Climate Change 93
2.6.2.1 Scenarios for Sea Level Rise 93
2.6.2.2 Results under Climate Change 98
2.6.3 Sensitivity Analysis 101
2.6.3.1 Probabilities 101
2.6.3.2 Time Horizon 104
2.6.3.3 Costs 106
2.6.3.4 Discount Rates 109
2.7 Value of Wetlands Protection in Context of SAV Restoration 111
2.8 Conclusions 112
2.9 References 114

Chapter 3 INTEGRATED SAMPLING OF THE ECONOMY AND THE ENVIRONMENT 117

3.1 Introduction 117
3.2 Objectives and Methodology 120
3.3 Overview of EVOI Theory and Applications 125
3.4 The Conceptual Model 133
3.5 Imperfect Information and the Choice of Standards 144
3.6 EVOI of Alternative Sampling Strategies 150
3.7 The Empirical Model 153
3.7.1 Creating the Corn Production Areas 154
3.7.2 Creating the Cornfields in the Watershed 159
3.7.3 Corn Yield Functions 161
3.7.4 Calibrating the Parameters of the Corn Production Model 161
3.7.5 Nitrogen Loading and Transport 164
3.7.6 Calibration of the Soil Retentivity Coefficients 166
3.7.7 Data Simulation 166
3.8 Sampling Strategies 171
3.9 Results 173
3.10 Sensitivity of EVOI to Alternative Sampling Strategies 174

3.11 Conclusion 177
3.12 References.. 178

LIST OF FIGURES

Figure 1–1: Schematic Presentation of an Adaptation Policy Framework (Source: Yohe, 2005). 33

Figure 2–1: Map of the case study site – Hampton Roads, South East Virginia 69

Figure 2–2: Effect of changing water depth on SAV location 69

Figure 2–3: Distribution of existing and historic abundance of SAV across the depth bands 71

Figure 3–1: Least cost solution for reducing pollution load 140

Figure 3–2: Least cost solution under productivity type heterogeneity 142

Figure 3–3: Least cost solution under pollution type heterogeneity 143

Figure 3–4: Cost minimizing efficiency of the three standards 150

Figure 3–5: Maps of the polygons (corn producing areas) in the Conestoga Watershed 157

Figure 3–6: Location of simulated cornfields in the Conestoga Watershed 160

LIST OF TABLES

Table 1–1: Key elements and their influence on timing 50

Table 2–1: Coverage area of existing SAV, historic abundance of SAV, and restoration region in each band, and of wetlands 89

Table 2–2: Restoration strategies, emergent SAV, and total SAV under baseline/'Without Climate Change' scenario 93

Table 2–3: Three scenarios of sea level rise 96

Table 2–4: The probability of sea level rise in this study 97

Table 2–5: Restoration strategies, emergent SAV, and total SAV under climate change 100

Table 2–6: Restoration strategies under climate change under different probability specifications 103

Table 2–7: Restoration strategies under climate change under different time horizons 105

Table 2–8: Restoration strategies for high cost and low cost 108

Table 2–9: Restoration strategies under different discount rate 110

Table 3–1: Information structures (I) 144

Table 3–2: Annual nitrogen loads for the 43 corn production areas in the CRW 158

Table 3–3: Corn yield function parameters for the agricultural capability classes 163

Table 3–4: Capability class based annual nitrogen loading and soil retentivity coefficients 166

Table 3–5: Specifications for the errors structures 170

Table 3–6: Value of information for alternative information structures 174

Table 3–7: Expected value of information under alternate sampling designs 176

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ESSAY 1

UNCERTAINTY AND CLIMATE CHANGE-IMPLICATIONS FOR ADAPTATION POLICY AND TIMING

1.1 Introduction

Adaptation is a key component in an integrated and balanced response to climate change and variability and has emerged as an integral part of domestic and international efforts in responding to the risks posed by climate change (Toman and Bierbaum, 1996; MacIver, 1998). The term 'adaptation' can be loosely defined as adjustments made in practices, processes, and structures that take account of changing climate conditions. Adaptation policy incorporates measures that either reduce the vulnerability of a system to climate change or take advantage of opportunities created by or enhanced by global climate change. In contrast to previous assessments, it was the Third Assessment Report (TAR) from the UN Intergovernmental Panel on Climate Change (IPCC) that first recognized potential adaptation responses and evaluated adaptive capacity of systems in dealing with the environmental, social and economic consequences of climate change (McCarthy et al., 2001). The TAR explicitly stated that adaptation was considered because plausible contemporary initiatives to limit emissions cannot stabilize atmospheric concentrations of greenhouse gases that drive climate change (Wigley, 1998) – Green house gas (GHG) concentrations reflect long term emissions and aggressive reductions in any one year have a trivial impact on the overall concentrations. The IPCC's Fourth Assessment Report (AR4) further states that, even without consideration of current emissions influence on future climate, adaptation will be necessary to address impacts from unavoidable warming resulting from past emissions (IPCC, 2007: Climate Change 2007: Impacts, Adaptation, and Vulnerability). Adaptation complements mitigation policies and the AR4 emphasizes that a mix of strategies that include both mitigation and adaptation can diminish the risks associated with climate change (IPCC, 2007: Climate Change 2007: Impacts, Adaptation, and Vulnerability).

Climate change researchers offer many arguments in their advocacy of deploying adaptive measures immediately. The last half century's pronounced climate variability and the increased occurrence of extreme events raises the concern that climate change could be more rapid, pronounced and unexpected than current day estimates suggests. Alternative climate risk modification strategies like adaptation is urgently needed if societies are to successfully deal with the problem of climate change. The TAR communicated the need for adaptation both at the regional and the global scale, across governmental and non-governmental organizations, and the AR4 adds to it by providing systematic assessments of adaptation practices, options, constraints, and capacity.

Advocacy of adaptation policy brings with it the responsibility of communicating methods for assessing, planning, and facilitating adaptation. Planners and managers who are at the helm of steering the process of adaptation through communities and managed sectors would require guidance on the design and adoption of adaptation policies. An obvious place to look for such guidance would be the literature on adaptation to climate change. However, a review of the literature reveals an overwhelming concentration on impact studies and potential adaptation strategies for selected sectors. This is not to say that the literature has lagged in terms of informing and advancing adaptation policy. On the contrary, given that the idea of adaptation as a response strategy to climate change first emerged just about a decade ago, the literature documents great advances that have been made by the climate change research community in terms of developing concepts, methods, framework, and case studies for assessing adaptation. But as the AR4 notes, a clear picture of adaptation's potential, limitation, or costs is still not available and literature assessed in the report does not indicate how effective various adaptation options are at reducing climate risks, especially at higher levels of warming and related impacts, and for vulnerable groups (IPCC, 2007:Summary for Policymakers).

There are primarily two reasons that impede the development of adaptation policies that can be confidently relied on. Firstly, effective adaptation measures (technological, behavioral, managerial, and regulatory) are highly dependent on specific, geographical and climate risk factors as well as institutional, political and financial constraints. It is a daunting task to evaluate the efficacy of the adaptation measures as the specificities of the system varies. Secondly, formidable informational challenges exist in terms of our knowledge of the systems (biophysical, human) and the climate change, and uncertainty is more so an issue when adaptation measures have to developed in highly specific geographical and social contexts. Consequently, dealing with uncertainty has been a big part of the climate change literature, with estimating the likelihood of future climate change becoming a priority objective within the adaptation research community (Dessai and Hulme, 2004).

Likelihood (probabilistic) assessment, which is essentially a way of incorporating uncertainty into environmental decision-making, is one avenue of exploring impacts of uncertainty on environmental decision-making. There are other aspects of uncertainty, particularly to do with the time path of resolution of the uncertainty, and how that interacts with elements like irreversibility and adjustments costs, that has implications for decision making under uncertainty. These aspects do impact the timing of decisions in environmental context, a fact that is explored, to an extent, in the economics literature under uncertainty (Pindyck, 2000, 2002; Arrow and Fisher, 1974; Fisher et al., 1972, 1974; Hanemann, 1989). However, works that explores the issue of uncertainty (and timing) in context of adaptation has remained limited (Ingham et al., 2007; Dessai and Hulme, 2007). The adaptation literature fails to adequately address the issue of timing of adaptation policies.

The overarching theme of the dissertation focuses on understanding the implications of uncertainty on environmental decision-making - Essay 1 explores the theme in context of adaptation to climate change. Essay 1 also takes a look at those characteristics of the adaptation problems, which when present with uncertainty, can either accelerate of delay the timing of adaptation measures. The timing issue is very important as the timing of the adaptation measures can affect the efficiency of adaptation as a policy response to climate change. Because adaptation problems are so closely defined by their context, the timing decision for adaptive measure will vary from problem to problem. The essay therefore concentrates broadly on the key elements that characterize problems of adaptation to climate change, to understand how the interactions between the elements can affect the timing of adaptation decisions. To do so, the essay primarily relies on literature review of two areas of social sciences (1) Uncertainty in Environmental economics, and (2) Adaptation to climate change. The former reveals the key economic issues (discount rate, irreversibility, non linearity in benefits and costs) relevant for policy decision making under uncertainty, and also shows that the net effect of interaction of these key elements tend to be model specific. The latter helps to establish the context specific nature of adaptation problems, and also highlights existing thoughts and approaches to dealing with uncertainty in adaptation to climate change. The essay explores the issues using varied examples of adaptation to climate change.

1.2. Objectives and Methodology

The primary objective of Essay 1, as stated in the previous section, is to understand how uncertainty can be dealt with in adaptation policy design. The specific objective is to address the implications of uncertainty surrounding climate change for the timing of adaptive measures. Many of the themes, elements, and issues relevant for uncertainty analysis in environmental problems have been discussed and documented in environmental literature, predominantly in the context of mitigation. There is no work that knits the independent themes together in structuring a decision framework that addresses all the key issues related to uncertainty in adaptation problems. The essay seeks to address that deficiency.

The essay uses a three-step approach to understanding how uncertainty impacts adaptation decision making, including timing. In the first step, the essay reviews the problem of uncertainty for policy design and evaluation in the subject area of environmental economics. In the second step, the essays reviews and synthesizes works on adaptation to climate change (from many subject areas) to understand (1) the breadth of adaptation problems, (2) approaches used for studying the problems, and (3) the extent to which uncertainty regarding climate change has already been addressed in these problems. Step 1 is intended to lay out the problems posed by uncertainty in a generalized framework for environmental decision-making, and step 2 is motivated with understanding the environmental context of bio physical and socio economic systems and processes in adaptation problems. In step 3, the findings from the previous two steps are integrated to synthesise the key elements that need to be considered in adaptation decision framework for evaluating optimal timing of the adaptation measures under uncertainty.

The rest of the essay is divided into the following sections. In section 1.3, the essay looks at the question of uncertainty in environmental economics (Step 1). Following Pindyck (2007), section 1.3 elucidates the three major complications (non linearity in environmental costs and benefits, irreversibility, and long time horizons) that make uncertainties in environmental problems more of an issue than other private and public policy decisions. Section 1.4 is a comprehensive review of the vast adaptation literature; key questions, issues, and problem areas of adaptation research are identified in this section (Step 2); it also includes a synthesis of the findings as guidelines for adaptation assessments and policy formulation. Section 1.5 builds upon the previous two sections; key elements are brought together and their combined direction of influence on the timing of adaptation is analyzed in context of different examples of adaptation to climate change (Step 3). The essay concludes in Section 1.6 with a note on how future researches can be refined to more systematically incorporate the issue of uncertainty and timing in adaptation analysis, assessments, and policy formulation.

1.3. Uncertainty in Environmental Economics

Under certainty, the economics of the design and evaluation of policies intended for environmental problems filters down to cost-benefit analysis. In a very simple framework, human indulge in activities that result in environmental degradation. Intervention, most often governmental, can stop the environmental degradation, but it does so at a cost. The policy problem boils down to an evaluation of whether the benefit from the policy (in terms of reduced environmental damages) is at least as large as the cost of the policy. When the costs and the benefits occur in the future, the analysis needs to be restated in present value terms; given a discount rate, the analysis simplifies to determining whether the net present value (NPV) of the policy (present value of benefits minus present value of cost), is positive or not. When comparing between many alternative policies, the optimal policy is the one with the highest NPV.

Uncertainty creates complication through three avenues - (1) Uncertainty in the benefits of the reduced damages (even in the amount by which the environmental damage is reduced), (2) uncertainty in the present and future costs, and (3) Discount rate uncertainty. Pindyck (2007) uses the example of climate change to elucidate the three avenues of uncertainty. He points out that no matter how much effort is invested in evaluating the benefits of mitigation policies, its precision would always be indeterminate as relationships between greenhouse gas (GHG) concentrations, regional and global temperatures, and climate patterns are partly stochastic. Even if the stochastic climatic processes could be determined, the social and economic impacts of reflexive human behavior (through reactive adaptation) are unknown. Similarly very little can be determined about the cost of the carbon tax, as long run behavior of consumers and producers are unknown. There is also no agreement among economists about the correct rate of discount that accounts properly for social time preference and risks.

Pindyck (2007) further argues that environmental problems under uncertainty are more challenging than problems in finance or other public policies that also deal with decision making under uncertainty because of three crucial additional complications. *Firstly, environmental costs and benefits functions tend to be highly non linear*. Damages from GHG emissions are low for low levels of pollution and then become severe at high levels (or even catastrophic beyond some uncertain threshold level). The same thing can happens with the costs of abatement. The non linearity is a serious complication as it prevents the use of expected values-the expected value of cost and benefit function are very different from the function of the expected value. Complicating the issue further is the fact that the *precise shapes of the functions are unknown*. This is an important consideration especially in problems where there is the possibility of a threshold or 'tipping points' at which the impact of the pollutant is severe, and nothing is known about the location of the point.

The second complication involves *irreversibility*, and there are two kinds of irreversibilities (economic and environmental) that work in opposite direction that are relevant for environmental economics. *Environmental (or ecological) irreversibility* usually refers to changes made on the environment that cannot be undone and will be experienced until perpetuity (total irreversibility) or for a very long period of time (partial). For example, the beauty of the Grand Canyon can never be recreated once it is destroyed or (as pointed out in the introduction) atmospheric accumulation of GHG is long lasting and it would take years for the levels to respond to drastic reduction. When irreversibility characterizes one of the alternatives in the problem, an extra value, an option value, attaches to the reversible alternative(s), i.e., an irreversible decision or action has to clear a higher hurdle to pass a benefit/cost test. Although it is not pursued in the essay, irreversibility and the notion of option value is well outline sin the literature (Arrow and Fisher, 1974; Fisher et al., 1972, 1974; Hanemann, 1987; Fisher, 2000).

The concept of *economic irreversibility* comes from the investment literature. Investment involving fixed capital like construction of plants or purchase of heavy machinery usually entails large costs, both upfront as well as operational. Depending on the nature of the investment, if for some reason (e.g. stochastic shocks to production) the usage of the capital has to be stopped prior to the time that will be required for the capital to naturally depreciate to zero, the capital has to be either abandoned or put to some other use. If the capital cannot be used in any other way, the costs incurred in its purchase are sunk costs that cannot be recovered-- the selling or disposal price of the purchased capital is zero. Almost all policies aimed at reducing environmental damage impose sunk costs on society.

Irreversibility matters only if there is uncertainty. Environmental irreversibility biases policies aimed at reducing environmental degradation to be more 'conservationist' than would be otherwise optimal. Economic irreversibility works in the opposite direction and tend to make environmental policies less 'conservationist'-sunk costs are permanent and cannot be undone in the future if the environmental resources obtained at the expense of this costs turn out to be of less value in the future. Both entail a possibility of severe regret, and greater the uncertainty, greater the scope of regret. The net effect of the irreversibilities tends to be model specific-Irreversibilities matter and it is important to evaluate how and to what extent they matter in problems.

The third problem in dealing with uncertainty stems from the fact that environmental problems tend to have very long time horizons, which exacerbates the problems of uncertainty over policy costs and benefits, but does so more for the discount rate. This is where problems of environmental economics differ most from capital investments problem in financial economics. NPV calculations for investment rarely go beyond twenty or twenty five years, whereas for environmental problems the benefits and the costs can accrue for over a hundred years or more. The longer the time horizon, the greater are the uncertainties, particularly to do so with discount rate-the present value of $ 100 for a 50 year horizon is $37 with a 2 % discount rate and $ 14 with a 4 % discount rate. For a 100-year horizon, the present value of $ 100 is $14 and $2 respectively. Simple calculations quickly reveal that with a rate of discount higher than 4 %, it would be difficult to justify any policy that imposes cost today but yields benefits hundred years hence.

Pindyck (2007) points out an important implication of discount rate uncertainty-the effective rate that should be used in NPV calculations should be less than the expected future discount rate. If R represents the (uncertain) discount rate, and R_e the expected value of R, then the expected present value of $ 100 received T years from now is $E[\$100/(1+R)^T]$, which is greater than $\$100/(1+R_e)^T$. The greater the value of T, greater will be the difference between $E[\$100/(1+R)^T]$ and $\$100/(1+R_e)^T$. Pindyck

(2007) illustrates the implication using the numerical example of wanting to evaluate the expected present value of a $ 100 benefit to be received 100 years from now, where the discount rate is uncertain and may turn out to be either zero or ten percent, each with probability ½ . The expected discount rate R_e is then 5%, and $ 100 evaluated at this rate yields a present value less than $ 1. However the expected present value of the benefit is higher than $ 1. If the true discount rate is zero, the present value of $ 100 is $100, and if the true discount rate is 10, then the present value of $ 100 is zero- together they yield $50 (1/2*100 +1/2*0) as the expected present value of $ 100. By back calculating, it can be shown that the effective discount rate that would result ina present value of $ 50 for $ 100 over 100 years is 0.7 percent. The example shows that even if the expected value of a discount rate is high (5%), uncertainty implies an effective discount rate of less than one percent.

Understanding the nature and extent of discount rate uncertainty is essential in evaluating policies that yield long term benefits. Pindyck (2007) concludes by stating that although past studies do not give us clear answer on the issue of which discount rate to use, it does establish two things - (1) the correct rate should decline over the horizon, and (2) the rate for the distant future is well below 2 %. 2 % is lower than what is generally used in environmental cost benefit analysis.

A good place to start exploration of the issue of optimal timing of policies under uncertainty is by understanding the way optimal timing problems have been approached in the literature. Optimal timing (or “stopping”) problems are an important class of stochastic control problems that arise in economics and finance, as well as in other fields. The theory of **optimal stopping** is concerned with the problem of choosing a time to take a particular action, in order to maximize (or minimize) an objective function (expected benefit or expected cost). Important examples include optimal exercise rules for financial options (e.g., finding the threshold price of a dividend-paying stock at which it is optimal to exercise a call option on that stock), and optimal capital investment and disinvestments decisions (e.g., finding the threshold prices of copper at which it is optimal to shut down an existing copper mine or invest in a new mine)-many applications also look at the aspect of technology adoption.

Stopping rule problems are associated with two objects - (1) A time sequence of random variables $X_1,X_2,...$, whose joint distribution is something assumed to be known, and (2) A sequence of 'reward' functions $(y_i)_{i\geq 1}$ which depend on the observed values of the random variables in 1i.e. $y_i = y_i(x_1,..,x_i)$. Given those objects, the problem is as follows: The decision-maker (DM) gets to observe the sequence of random variables, and at each step i, the DM can choose to either stop observing or continue. If the DM stops observing, the DM receives reward y_i. Optimality calls for the DM to choose a stopping rule that maximizes the DM's expected reward (or equivalently, minimizes expected loss). Put differently, optimal stopping problems arise in the case of an uncertain situation where the decision-maker at each successive interval of time must take one of two decisions- either to irreversibly stop the process or to allow it to continue. Decisions to stop results in a reward (that is conditional on the current state of the process), and costs are incurred for continuing. The objective is to stop at the 'best' time from the view point of maximizing average reward, and the solution is rule that tells the DM when the process should be stopped. A good review of applications of optimal stopping problems in economics can be found in (Clarke and Reed, 1990).

Optimal stopping problem formulation for climate policy presents a unique challenge as it is characterized by the presences of not only uncertainty and irreversibility, but actually two irreversibilities that operate in opposite directions. Continuous time representation of the stopping problem has been adopted by Pindyck (2000, 2002) to examine the effect of uncertainty over both future benefits from reduced GHG concentration and evolution of the concentrations on the timing of a policy that calls for permanent reductions in emission. There are sunk costs for policy adoption, which once expended are not recoverable. Pindyck (2002) finds that within a 'reasonable' set of parameters, such uncertainty results in a higher threshold for policy adoption (and also less stringent emission reduction) – policies will be delayed. The reason for this result is the way the model is set up- policy adoption imposes a sunk cost over the entire trajectory of future emissions whereas inaction in any small time period just causes continued emissions only over that period.

Within the same framework, Pindyck (2002) also explores how the two irreversibilities, economic (involving sunk costs of policy adoption) and environmental (involving partially or totally irreversible damage), interacts with the uncertainties in (1) the future benefits and costs arising from the policy adoption, and (2) uncertainty in the evolution of the environmental system to influence the timing decision of the policies. There are also other studies that examine the effect of uncertainty and opposing irreversibilities of the policy adoption decision, although they do so in a two period simplified framework (Kolstad, 1996a, 1996b; Fisher and Narain, 2003). All these studies find, at least with the context of emission abatement policies aimed at global warming, that the investment (economic) irreversibility effect is much larger than the GHG (environmental) irreversibility effect- uncertainty over the impacts of climate change leads to a reduction in first period abatement or a delay in the adoption of the policy. Near term policies tend to be less 'conservationist'. The studies mentioned above do not include the possibility of a catastrophic event in their formulation. The few studies that did consider the possibility of catastrophic impacts of GHG accumulations find that the presence of catastrophic events can lead to earlier and more stringent abatement policies, but only if (1) the likelihood of the catastrophe (the hazard rate) increases sufficiently with the stock of the pollutant (Clarke and Reed, 1994) or (2) if we assume that there is a critical level of stock accumulation at which catastrophic event is triggered and that level is unknown (Tsur and Zemel, 1996). Where does this leave us when we consider uncertainty, irreversibility, and catastrophic event- the answer is not clear.

Uncertainty remains central to environmental policy. Although there is now a clear understanding of how non-linearities and irreversibilities might result in policies based on cost benefit analysis to be misleading, there is no alternative clear approach or rule of thumb for adapting environmental policies to uncertainty. Most past studies that do not consider catastrophic favors waiting over early action (resulting from the dominance of economic irreversibility), but the inclusion of catastrophes into studies may alter that. Further research into the causes and likelihood of severe or catastrophic outcomes, and also to costs and benefit functions of other environmental problems could throw light on more conclusive approaches to dealing with uncertainty in environmental economics.

1.4. Brief Overview of Adaptation Literature

The importance of adaptation as policy option or response strategy was much discussed in climate change literature in the last decade. The 1998 IPCC workshop on Adaptation to Climate Variability and Change initiated discussions on a wide variety of issues ranging from conceptualizing adaptation, to designing frameworks for addressing key questions and mechanism of adaptation, to methods for assessing social vulnerability and resilience to climate impacts (IPCC, 1998). The workshop proceedings were later more formally developed in IPCC's Third Assessment Report (McCarthy et al., 2001). Major journals on environmental and climatic research ran special issues on adaptation to climate change (Maciver and Dallmeier, 2000; Klein and MacIver, 1999). A special issue of *Climatic Change* (Kane and Yohe, 2000) brought together newer papers on societal adaptation to climate variability and change with focus on understanding societal ability to make climate policies more responsive to the dynamics of change. AR4 (2007), the Fourth Assessment Report of IPCC summarizes the advancement made in the study of the impacts, adaptation, and vulnerability since the publication of TAR.

It was the literature on climate impact assessment that is credited with early on recognizing the role of adaptation in climate change. First generation impacts assessments were greatly criticized for neglecting adaptive potential in their assessment set up. Impact assessments studies that fail to consider adaptive potential are likely to overestimate the costs of climatic impacts (Reilly and Schimmelpfennig, 2000).

Understanding what adaptations will be likely becomes an important part of impact assessment. The hypothesis of what adaptation becomes likely used in early impacts assessment studies were more assumed than tested or based on a thorough investigation of the adaptation system. Varied assumptions made about the characteristics of the system of adaptation and the participants in it resulted in widely divergent views on the impacts of climate change.

To get impacts right it was important to get a realistic picture of adaptability. This resulted in adaptation being studied with more observed, explicit, and testable specification of system characteristics and the process of adaptation. The approach shifted from assuming adaptation in a system to determining adaptation that would most likely evolve in a system based on a thorough understanding and study of system characteristics.

Early researchers developed the study of adaptation along the avenues of three awareness questions: - (1) Adapt to what? (2) Who or what adapts?, (3) How does adaptation occur in a system (Smit et al., 1999)? When information issues were brought into the picture, additional questions evolved about who knows what about climate change, when do they know it, and how do people learn from new information (Yohe and Neuman, 1997; Bryant et al., 2000; De Loe and Kreutzwiser, 2000; Lempert et al., 2000; Miller, 2000; Reilly and Schimmelpfennig, 2000; Schneider et al., 2000? Researchers also looked at how are resources used for adaptation (Wheaton and MacIver, 1999)? Answers to these questions guided the development of a framework for studying adaptation.

1.4.1 Adapt to What?

In responding to the ‘adapt to what’, it was recognized that adaptation essentially implied a response to some manifestation of climatic stimuli. The stimuli can be expressed in terms of weather and climate conditions (long term mean climate variables like annual average temperature or precipitation). They can also be manifested in terms of ecological effects or human impacts from climatic conditions (droughts and floods). Smit et al. outline three broad temporal categories of climatic conditions to which adaptations are considered (Smit et al., 1999). The three broad categories are (1) Climate change as reflected in long term trends or scenarios pertaining to mean temperatures and related climate ‘norms’, (2) Climate variability around norms over multi-year periods as reflected in shifts and changes in the shape of the frequency/probability distribution of the relevant climate variables for a system (e.g., manifested in recurring anomalies), and (3) Isolated extreme events such as droughts, floods, and storms.

Debate exists on whether climate change implies a shift in the distribution with unchanged variability (i.e., the mean value of the climatic attribute changes while the variance of the distribution stays the same) or whether the distribution shifts with changed variability (i.e., both the mean and the variance changes). The fact remains that even with unchanged variability and constant coping range, a minor shift in the mean can increase (or decrease) the frequency of occurrence of extreme events (Smit et al., 1999; Smit et al., 2000). Changes in variance would further increase (or decrease) the frequency of occurrence of (what now are concerned) extreme events-e.g., in Fisher and Rubio (1997), the authors find that increased uncertainty (modeled with increased variability) results in increase in the long run equilibrium water storage capacity, provided the marginal benefit of water withdrawal is convex. Therefore it is important that adaptation assessment consider adaptation to climate variability in addition to changes in mean conditions.

To address climate variability, it becomes important to identify natural variability under current climate that serves as a baseline to understand future changes in variability. However, herein lies a challenge as establishing baselines for natural variability under current climate is difficult as the variability computation using historical data is very sensitive to the range of time period selected for variability analysis. The challenge is in distinguishing true climate variability from the noise surrounding it. The inability to distinguish noise raises the concern that noise regarding the natural variability may conceal its true long-term trend, thereby urging society to maladapt or delay adaptation until it is too late (Lempert et al., 2000). For quality decision-making, it is necessary that decision makers have the ability to monitor signals that can be attributed to climate change amidst the noise of climate variability (Bryant et al., 2000; Schneider et al., 2000; Smit et al., 2000). The literature lays down the importance of considering both climate change and climate variability but does not provide a systematic way of discerning the two climatic stimuli.

1.4.2 Who or what Adapts? - System Characteristics

The question of "who or what adapts?" relates to the unit or the system of analysis in adaptation studies. Systematic treatment of adaptation requires clear delineation of the system of interest and clear definition of the participants and their roles in the adaptation process (Smit et al., 1999). Adaptation can imply adaptation in specie or in an ecosystem in a region, or an industry (agriculture, fishing, and utility providers) or a community, or by a private individual or a public institution, or adaptation across a social structure or a political entity in the region. The question of 'who or what adapts?' mostly focuses attention on the characteristics of the system of adaptation. Adaptation depends fundamentally on the system's characteristics that determine the system's propensity and capacity to adapt.

Developing consistent definitions of system characteristics dominated much of early adaptation research. A multitude of terms has been developed in the literature to describe system characteristics, many of them interrelated and indistinguishable from others. Table 1 in Smit et al. (2000) report more than a dozen of these terms with their definitions. The terms sensitivity, coping range, vulnerability, and adaptive capacity are terms that are frequently used in the climate debate. Formal definitions of these terms are available in TAR (McCarthy et al., 2001), and also in the AR4. *Sensitivity* is the degree to which a system is affected by (or is responsive to, either adversely or beneficially) a climate related stimuli. The effect may be direct result of changes in climate stimuli (like changes in crop yield due to changes in climate mean, variability or extremes) or it may be indirect consequences of changes in climate (like damage to coastal property from increased frequency of storm surge due to sea level rise) (Burton et al., 2002). *Coping range* refers to the inherent capacity that exists in most social and economic systems to accommodate deviations from the normal conditions, excluding extremes. The coping range varies across systems and geographic regions and is not static. It changes with newer adaptations in the system. *Adaptive capacity* refers to a system's ability to deal with all kinds of climatic stimuli, including variability and extremes, to cope with both beneficial and damaging consequences of climate change. Included in adaptive capacity is the coping range; coping range can be conceived as adaptive capacity to current climate and variability. Adaptive capacity therefore includes the ability of a system to adapt inherent in the existing coping range as well as the ability to expand the coping range with new adaptations. Measures to increase adaptive capacity enhance the coping range and vice versa. Coping range marks the vulnerability or damage thresholds of a system to a given climate-a system becomes vulnerable when it is subject to climatic impacts that cannot be accommodated by the coping range (Pittock and Jones, 2000).

Vulnerability in TAR (and AR4) is defined as "the extent to which a natural or a social system is susceptible to sustaining damage from climate change". It refers to the degree to which a system is unable to cope with the adverse effects of climate change, including variability and extremes. Vulnerability of a system is a function of the sensitivity of the system to climate change, its adaptive capacity, and the character, magnitude, and rate of climate change and variability to which the system is exposed (Burton et al., 2002; AR4). A simplified but useful formulation is provided by Burton et. al. (2002) - Vulnerability is a function of impacts and adaptation Impacts are determined by the kind of climate the system is exposed to (e.g. more frequent droughts) and how resistant or robust the system is to the climatic changes (e.g. the system has more drought resistant crops). Adaptation depends on the underlying (existing) adaptive capacity of the system and the ability to utilize it in the creation of future adaptive measures that helps it to counter the net impacts on the system. A highly vulnerable system will be one that is highly sensitive to small changes in climate while being constrained in the ability to adapt.

A resilient system on the other hand is one that is not sensitive to climate change and has a capacity to adapt-resilience is the flip side of vulnerability.

Later adaptation research moved away from the aspect of informing impact assessment and focused on the question of how and where to deploy adaptation responses to climate risk. The new research agenda shifted the emphasis on understanding the determinants of vulnerability and adaptive capacity. Acceptable risk of a system was formalized in the TAR as a function of hazards and vulnerability i.e.

(1.1) Acceptable Risk = f (hazards, vulnerability)

Yohe and Tol provides additional structure to the TAR suggested functional relationship in the form of Equation (2) (Yohe and Tol 2002).

(1.2) $$V = F\{E(A); S(A)\}$$

where, V stands for vulnerability, E for exposure, S for sensitivity and A represents adaptive capacity. A is further defined as

(1.3) $$A = AC(D_1;.......;D_8)$$

Where D_i , i()8, are the eight determinants discussed in chapter 18 of the TAR.

The TAR identified determinants of adaptive capacity, listed by Yohe and Tol are- (1) The range of available technological options for adaptation, (2) Resource availability and distribution across population, (3) Social infrastructure- to what extent are resources accessible to the decision makers and stakeholders, (4) Stock of human capital including education and personal security, (5) Stock of social capital with clear delineation of property rights, (6) Availability of risk-spreading processes in the system,

(7) The ability to distinguish credible information from the non credible kind and (8) The public's perception of the source of the climatic stress, and the significance of the local manifestations of the climatic stress. The authors further develop a method that evaluates the efficacy and feasibility of a given adaptation option in terms of these determinants to judge the potential contribution of the adaptation option to coping capacity.

The elucidation on the different terminologies makes clear one important distinction- adaptation that is rooted in the expansion or refinement of existing resources and institutions (those included in the coping range) and adaptation that involves creation of new resources and institutions (outside the coping range). For example, possible adaptation options for the ski industry include expansion of snow making capacity (which is rooted in current snow making technologies and possible expansion or refinement of it), and also buying weather derivatives. The former represents the kind of adaptation that should be included in impact assessments to inform vulnerability-they represent adaptations that are currently in the system and would possibly emerge in the system in the future in expanding the coping range. The latter are adaptations that would need to be considered when a system is found vulnerable after its coping range had been fully employed. Both adaptations reduce vulnerability to future climate risks, but one does so by enhancing the coping range and the other does it by reducing vulnerabilities when it cannot be handled by the enhanced coping range.

1.4.3. How does Adaptation Occur?

This question of 'how does adaptation occur?' refers both to the processes of adaptation and the forms of adaptation that arises (Smit et al., 1999). The authors categorize adaptation based on attributes of purposefulness, time when it occurs, temporal and spatial scope. Corresponding to these attributes adaptation can be autonomous (spontaneous) or planned, anticipatory or responsive (ex ante or ex post) to the climatic stimuli, short-term or long-term, and localized or widespread. Depending on the form of the adaptive measures, adaptation may be structural, institutional, legal, regulatory, financial or technological. Adaptation may also be defined based on performance attributes like cost effectiveness, efficiency, equity, and implementability- Smit et al, note that performance attributes are often central features of evaluation of adaptation options.

Smit et al., (2000) summarizes three broad approaches of understanding the process of adaptation- (1) Conceptual models of adaptation processes that specify sequential relationships between the stressors, the vulnerability of the systems, short term autonomous adaptation, initial impacts, long termed planned adaptation, and net impacts, (2) Numerical Impact Assessment Models that include adaptation via assumptions, which are determined from theoretical principles, observations of systems under stress, and hypotheses or conjectures of the scientific community, and (3) Empirical Adaptation Studies that attempt to better understand the nature and processes of adaptation by observing , documenting, and reconstructing current and past adaptation to climate change.

Not much documentation exists for empirical adaptation studies at regional levels. Because impact assessment models are restricted in the degree to which they can accommodate adaptation in their set-up, conceptual models of adaptation processes work best in understanding the role of adaptation as a risk management strategy. However conceptual models must be designed with care if they are to be used for understanding how adaptation occurs in the system. The models must capture as best as possible systems characteristics, the set of all plausible future climates, the state of knowledge and degree of belief about future climate change within the system, and the system's endowments or resources that will become available for facilitating adaptation. Widely varying permutations of future scenarios must be incorporated to account for unanticipated surprises that can occur in the climate, social, political, and economic systems-the emphasis is on many integrated climate and socioeconomic scenario analysis and not on climate scenarios only. Since a lot is currently not known, conceptual models will have to advance analysis making various assumptions. The models must conduct adequate sensitivity analysis of the assumptions to determine robustness of results.

1.4.4 Modification of 'Adapt to What?'

Increasingly, it has been argued by climate change researchers that adaptation should not be restricted to adaptation to climate stimulus only. Climate is not the only environmental stress on a system at any point of time and it is not the sole driver of all changes. In a dynamic world, many factors change simultaneously and not necessarily independently. Barker (2003) points out that TAR uses the traditional "cause and effect" approach developed in the integrated assessment literature. The climate scenario drove the biophysical impacts that in turn impacted the socioeconomic set up necessitating adaptation within the system. He proposes 'systems thinking' as an alternative approach. Under systems thinking, more emphasis is given to the combined effects of multiple interactive stressors and climate is one of them rather than being the sole driver of all change in a system. The changes in the climate system in the systems approach are studied in conjunction with (1) changes in the biophysical and socioeconomic systems under (2) different policy regimes pertaining both to climate and the management of the other drivers. The systems approach is very appropriate for studying regional adaptation problems as local decision-makers deal with management issues that involve simultaneous consideration of many environmental stressors and changing market and social conditions. However, to do, research would have to predominantly depend upon scenario analysis as probabilistic assessments of systems other than climate are very difficult.

Given that changes in the future socioeconomic systems are as important as changes in the climate systems, future socioeconomic scenarios will have to be designed carefully. This requires a good understanding of dynamic changes in socioeconomic systems and reasonable predictive power of where the current changes are headed in the future. In addition it requires some foresight into understanding whether and to what degree market and people will anticipate some of the impacts of climate on human systems and adjust proactively-this is where the component of human reflexive behavior come into the analysis that in general cannot be predicted. Scenarios that serve early detection and evaluation of adaptive capacity need to be developed (Parry 2002).

1.4.5 Costs and Benefits of Adaptation

Evaluating the costs and benefits of adaptation is important in understanding (1) whether a particular adaptation option is worth its benefits in costs and (2) how to prioritize among the many adaptation options that become available in a system. Tol et al. (1998) reviewed the literature on climate change impacts to seek insights into the scope and the likely costs of adaptation. They discovered that the effectiveness of adaptation was an open issue in the economic sense as the costs and benefits of the adaptive measures were not addressed in the impact literature. Few works deal with the issue of adaptation costs and studies on the benefits of adaptation are practically non-existent. AR4 notes that comprehensive multi sector estimates of adaptation costs and benefits are currently lacking although there are some benefit cost estimates at regional and project level available for sea level rise, agriculture, energy demand for heating and cooling, and water resource management (Adger et al., 2007).

In addressing the costs and benefits of adaptation certain key aspects need to be remembered. Autonomous adaptation cost is an important aspect of studies on evaluation of adaptation policy initiatives as they form the baseline for what costs of adaptation will be under the "no planned adaptation" or "do nothing" scenario. In analyzing the costs, many argue against the "equilibrium to equilibrium" (i.e. comparing costs of adaptation under current climate and then under the new climate) approach of computing adaptation costs stating that it fails to account for the transition costs. Adaptation costs must account for the transitory costs of not only the direct costs of adaptation but also the indirect costs of adapting to the adaptations (Kates, 2000). For example, institutions matter significantly in the adaptation process as they can either promote or impede the timely flow of information (Kates, 2000; Miller, 2000). Institutions might have to be restructured in order to facilitate adaptation. The indirect cost of such restructuring is also a cost of adaptation. Institutional and other transitory changes (behavioral, structural) that determine the costs of adaptation necessitate the inclusion of more transitory or "in between" scenarios of adaptation.

Data gaps also hamper the estimation of the costs and the benefits of adaptation, undermining the use of cost benefit or cost effectiveness as criteria for adaptation evaluation analyses. It must also be noted that economic viability alone is not a sufficient criterion for judging adaptation options. Ease of facilitation, implementability, flexibility, acceptability, and sustainability of adaptation options are equally important in evaluating the adaptation options and measures. Adjustment costs have a role to play too in adaptation decisions but that discussion is reserved for Section 1.5 in which the timing issue is explored.

1.4.6 Vulnerability Revisited

Burton et al. (2002) distinguish between the 'first generation' and 'second generation' of adaptation research. As noted earlier, the first generation of adaptation research was conducted with the purpose of informing impact assessment and mitigation policy. Consequently, first generation adaptation research is overtly focused on biophysical impacts and is less developed in terms of socioeconomic impacts. The second generation of adaptation research conducts adaptation research with the purpose of informing adaptation policy. One consequence of the shift in research from 'adaptation as a part of impact assessment' to 'adaptation as a policy' has been the emergence of vulnerability as a central concept of adaptation research (Burton et al., 2002).

Vulnerability has been widely studied in the past few years. Criticizing the traditional IPCC impact assessments that focus on biophysical vulnerability, (Handmer et al., 1999) argue that human behavior, institutional capacity, and culture (which relate to social and economic vulnerability) are more important than just biophysical vulnerability. They find that although at the broad global scale, human societies are strongly adaptive; the story is different at local levels. At the aggregate level, a region may not be vulnerable to climate change, but specific populations within it (e.g. people living on the coast or on small islands) may be extremely vulnerable to climate change at their current locations. (Adger and Kelly, 1999) reinforces the point that vulnerability is population specific- the authors argue that vulnerability or security for a population group is closely tied to their access to resources and their entitlement to call upon these resources-it has often been found that the groups most vulnerable are least endowed with resources to deal with climatic impacts. Less endowed groups at risk will have to aided from outside. Vulnerability assessments have to consider this aspect because adaptation cannot be achieved without the availability of resources.

It must be stated that most of the work related to vulnerability and adaptation was achieved in the context of case studies conducted at national or sub national levels for mainly sectors like agriculture(Mortimore and Adams 2001;Reilly and Schimmelpfennig 1999; Kelly and Adger 2000; Luers et al. 2003; Vasquez-Leon et al. 2003), insurance (Tucker 1997; Tol 1998), coastal systems (Yohe and Neuman 1997; Klein et al. 1999; West et al. 2001)and water (Frederick 1997; Loe et al. 2001). These studies are rich in yielding the contrast between the developed and developing nations in terms of institutional arrangements, access to information and resources, and entitlement structure that affect their coping abilities to environmental change. Kelly and Adger (2000) provide good insight into planning adaptation for communities that differ widely in their composition, and elaborate on existing theory and practice in vulnerability assessment. A noteworthy paper is that of Luers et al (2003) in which the authors propose a method for quantifying vulnerability.

The focus on vulnerability has led to a bifurcation in literature on the approaches used to inform climate adaptation policy. The first approach, called 'top-down' or biophysical vulnerability approach, has been used predominantly in impact and adaptation assessment studies. Parry and Carter (1998) describes the approach as a prediction-oriented approach that considers a single or a range of world development scenarios, whose greenhouse gas emissions serve as inputs to global climate models (GCMs), whose output serves as input to impact models. Anticipatory adaptation strategies are then studied in decision-making frameworks that look at the impacts of climate change on the exposure unit being examined. The second approach, called 'bottom-up' or social vulnerability approach focuses on present day climate variability as a good proxy for near-term climate change and studies present day ability or adaptive capacity (determined mostly by indicators like economic resources, technology, infrastructure, institutions, equity, and information & skills) of individuals or social groups to respond to (cope with, adapt) stress on their livelihood and well-being to understand adaptation to climate change. The two approaches differ in (1) type and scale of the unit of analysis, (2) planning horizon considered, and (3) in the motivation of the analysis. Biophysical vulnerability scholars deal with physical or natural units like watersheds, ecosystems, and irrigation projects while social vulnerability scholars prefer exposure units like households and communities. Social vulnerability scholars concentrate on past and present experiences to inform adaptation policy for today and the near future whereas biophysical vulnerability scholars typically focus on mid term and long term future. The former are also more interested in the understanding the processes underlying vulnerability, while the latter is motivated to model the impacts of climate change with as much precision as possible. Although both approaches inform adaptation policy (via informing vulnerability), they have different information requirement- the 'top down' approach could do with more research on the likelihoods of climate change, while the 'bottom up' approach would benefit from more research on future scenarios for analysis. Together, they can be collectively used to improve adaptation decision making under uncertainty, a point that would be elaborated more in Section 1.4.8 where the issue of uncertainty in adaptation context id explored in more details.

1.4.7 New Model for Adaptation Assessment

Parson et al. (2003) propose a new institutional model for adaptation assessment that connects scientists, resource managers and stakeholders in regional efforts that integrate observations, data, research, and applications. The emphasis is on identifying key regional issues, characterizing **relevant uncertainties**, and assessing adaptation response. Regional approaches are advocated as knowledge and data of region specific resources, vulnerabilities, management priorities, and adaptation options enable effective development of socioeconomic scenarios of required level of detail. By promoting sustained relationships with stakeholders, resource managers, industry personnel and planning authorities, the regional approach paves the way for continued assessments and easy implementation of adaptation options.

United Nation's Development Program's (UNDP) Adaptation Policy Framework (APF) provides another way of approaching systematic adaptation policy development (Lim and Spanger-Siegfried, 2004). The APF was developed with the objective of providing guidance on the design and implementation of projects that promote national strategies for adaptation in a sustainable development context. The APF was established with the aim of pursuing five important objectives: increasing the robustness of infrastructure designs and long-lived investments; enhancing the flexibility and resilience of managed natural and social systems; increasing the opportunities of autonomous adaptation of unmanaged natural systems; reversing maladaptive trends; and finally improving societal awareness and preparedness for future climate change and variability. Adaptation policy needs to be directed at sectors of the economy that are of national importance or at specific regions of the country or groups of people that are vulnerable to extreme climatic events like storm surges, floods, and droughts. Irrespective of where adaptation policy is targeted, it is contended that its implementation will be severely limited unless adaptation is placed in the socio political context. The authors consequently recommend that adaptation be incorporated into a country's national planning process and developed in context of other economic or environmental policies.

The UNDP's framework builds on and emphasizes on the following five principles - (1) Adaptation policy and measures are best addressed in a developmental context, (2) Adaptation to short-term climate variability and extreme events are explicitly included as a step toward reducing vulnerability to longer-term climate change, (3) Adaptation occurs at different levels in society, including the local level, (4) The adaptation strategy and the process by which it is implemented are equally important, and include effort for reviewing, evaluating, and monitoring adaptation, and finally, (5) Building adaptive capacity to current climate is one way of preparing society to cope better with future climate. Many of these principles are based on suggestion from the adaptation literature.

The last principle, which calls for vulnerability and adaptation assessments to current climate, is one of the most innovative features of the Adaptation policy Framework. By necessitating the assessment of current conditions, the principle ensures two things. First, it establishes present levels of adaptation to current climate risks as the 'adaptation baseline' to which improvements in adaptation can be systematically compared to in order to monitor the effectiveness of the improvements. Secondly, the principle ensures that all resulting policies and measures are firmly rooted in current experience. The APF therefore combines the better of the two approaches (top down, bottom up) to studying vulnerabilities.

The detail or the depth of guidance needed in any adaptation system will depend upon the level of knowledge about vulnerability and the degree of experience at handling adaptation to climatic stimuli in the system. The APF lists the five major cross cutting components that may be used either individually or all together in informing the adaptation process. Figure 1-1 presents a sequential diagram of the major components developed within the APF framework providing details for each component. The APF is supported by a series of nine technical papers that provide detailed guidance on each of the APF components. Careful implementation of the APF will invariably involve careful application of the scoping and design of the adaptation process, strong stakeholder engagement, assessing and enhancing adaptive capacity, analysis of adaptation to cope with current and future climate change, and a program to monitor, evaluate and improve the impact of the adaptation activity.

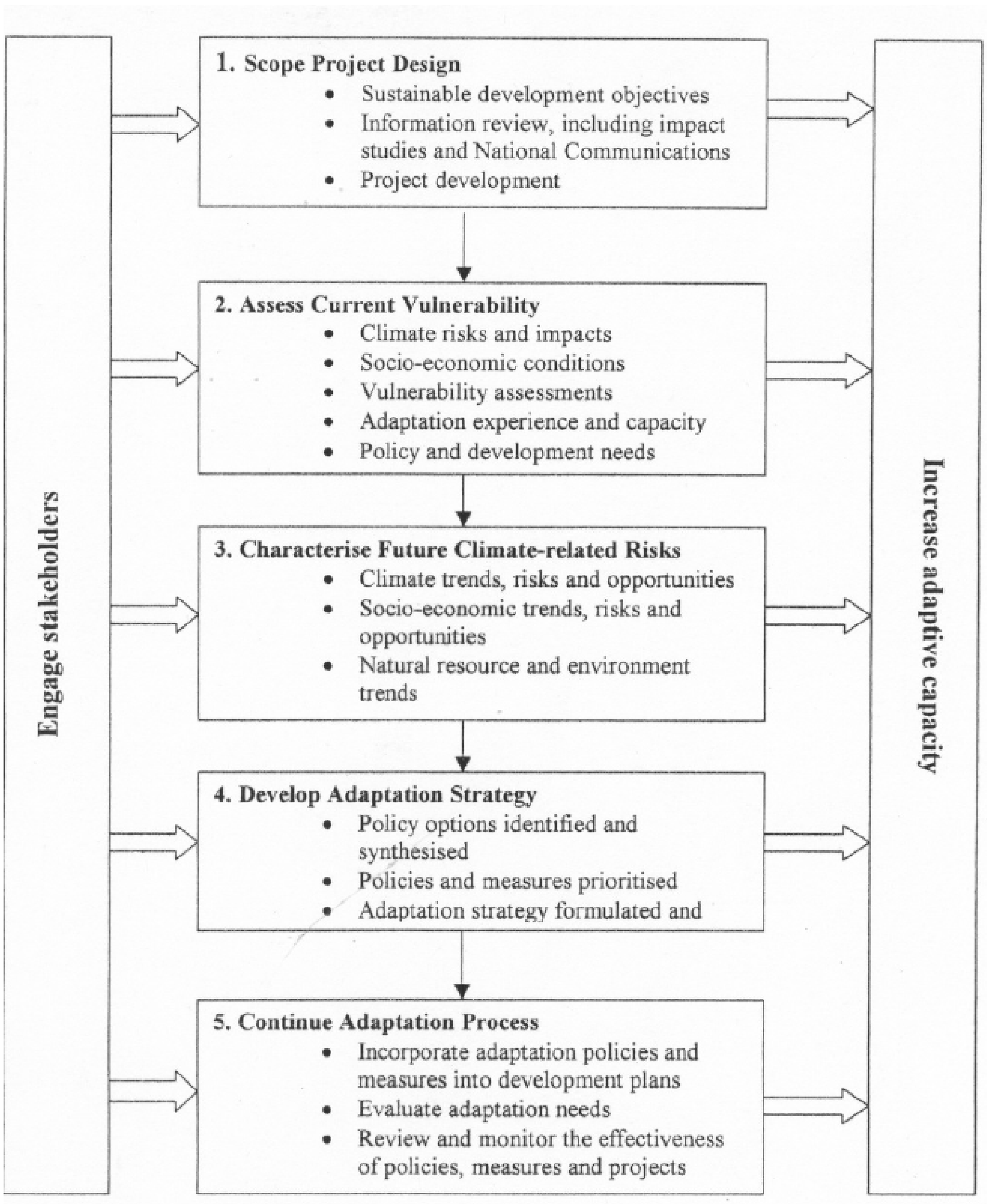

Figure 1-1: Schematic Presentation of an Adaptation Policy Framework. (Source: Yohe, 2005)

In summary, this is what the literature offers on framing adaptation research problem and policy. Adaptation policy will have to be based on adaptation measures that are operational at the local level. Assessments of climate risks and vulnerability begin with assessments of current climate risks, current coping capacity, and socioeconomic vulnerabilities. Having assessments rooted in present conditions enable understanding of how current conditions can be modified to deal with future climate risks. Adaptation options should be evaluated not on the basis of benefits and costs involved alone but also with due consideration for their implementability and adoptability in society. The best route to developing adaptation policy is finding ways of incorporating adaptation in existing policies.

A key emphasis in adaptation policy is on continued evaluation of adaptation strategies. With so much uncertainty existing over future climate change, it will not be appropriate to conceive and implement an adaptation policy as a one-time deed. For adaptation policies to be efficient, they have to be constantly evaluated on their performance and modified in light of newly arriving climate information. There are major differences between theoretically conceiving of a policy and actually implementing it. Tracking how the policy performs in reality is essential to ensure that modifications in the policies and measures can be made as and when required. Continued assessments of adaptation policies and measures are an integral part of APF that ensure that adaptation to climate change remains on the right track. This has important implications for how adaptation policy assessments are formulated- adaptation policies need not be conceived as a one time deed but can be formulated as incremental pieces of the same policy. The point will be taken up in more details in Section 1.5 when the timing issues id explored.

1.4.8 Uncertainty and Adaptation

Scientific understanding about climate change, its impacts, and the response of the systems to climatic impacts is uncertain and evolving. It is by now an accepted fact that any adaptation analysis will have to deal with uncertainty. Many papers explored the implications of climate uncertainty for adaptation policy choices (Yohe et al., 1996; Yohe and Neuman, 1997; Yohe and Schlesinger, 1998; Lempert et al., 2000). Recent papers directly take on the issues that uncertainty poses for climate policy (like downscaling of GCM models for regional analysis, spatial interpolation of climate for places where historical data do not exist) and find innovative scientific methods for dealing with those issues (Paoli and Bass, 1997).

Dessai and Hulme (2004) note that estimating the likelihood of future climate change has become an objective within the research community, driven by advancements made in science and increased user demand, and because of the central role played by climate prediction in guiding adaptation policy. This prompted the authors to question whether climate policy needs probabilities or not. There has been much debate about whether probabilities are useful for climate change policy, with some researchers being of the opinion that all possible future scenarios must be considered, and not the likeliest one (Schneider, 2001; Grubler and Nakicenovic, 2001; Pittock et al., 2001). Others point out that mere knowledge of the probabilities is not sufficient in adaptation context, as reflexive human behavior (i.e. actions explicitly influenced by information) is largely intractable in context of prediction (Dessai and Hulme, 2004).

They note that the case for whether probabilities are needed or not depend upon the approach taken for studying adaptation- ‘top down’ or biophysical vulnerability approach, driven by results from GCM’s, have more informational requirement than ‘bottoms down’ or social vulnerability approaches that are rooted in past and current experiences. They argue that planned or anticipatory and strategic adaptation, the kind undertaken by public decision-makers, would be greatly helped by knowledge of probabilities. On the other hand, autonomous, instantaneous, responsive adaptation, undertaken by private decision- makers (humans, managed ecological systems), based on experiencing climate hazards and responding to them, rather than planning in advance, will not benefit from probabilistic information.

Dessai and Hulme (2004) characterize uncertainty in context of climate change into three different types- (1) Epistemic, (2) Natural Stochastic, and (3) Human reflexive. Epistemic uncertainty originates from incomplete knowledge of the processes that influence events. In climate change, this type of uncertainty includes unknown values for climate sensitivity, the rate of heat uptake by the deep oceans, and the parameterization of an impact model. Collecting more information can reduce (or increase) epistemic uncertainty. It is possible and acceptable to use probabilities to represent uncertainty, but the representation will be limited by the extent of the knowledge thereby allowing for subjective element entering the analysis. Stochastic uncertainty is driven both by incomplete knowledge and unknowable knowledge and stems from variability in known (or observable) populations, and therefore represents randomness in samples. This type of uncertainty arises when the aim is to predict chaotic variable like climate and weather, which are stochastic and unpredictable. Stochastic uncertainty can be represented by probabilities but within limits-current representation of this uncertainty in literature is not fully probabilistic and this is because of computational constraints. The authors emphasize on the third kind of uncertainty and state that scenario analysis and not probabilistic representation would be the approach to dealing with reflexive uncertainty. Human reflexive uncertainty stems from the understanding that humans are capable of reflecting critically on the implications of their behavior and making adjustments in the light of experience. In context of climate change, it means human being will react either by taking measures that aid mitigation and adaptation. If we currently have an estimate of the likelihood of future climate change in place, the reactive actions of human will alter the original estimation of the likelihood. Probabilities, if used, will only be provisional in this case and uncertainty is irreducible in the context of prediction. Modeling reflexivity (iterative human behavior) is fundamentally complex and it is impossible to model it in ways that can lend it to predictions. The authors conclude by stating that a hybrid approach that combines probabilities (to represent epistemic and natural stochastic uncertainty) and formal scenario methods of the 'what if' type of question (to represent human reflexive uncertainty) be used to organize inquiry, identify interdependencies, and develop a better understanding of the complex issue of climate change and adaptation. The importance of sensitivity analysis (that answers questions like how sensitive is a particular system to changing probabilities in climate? and how sensitive are the adaptations decisions within the system to upstream uncertainties from emission scenarios and impact modeling?), is sometimes forgotten in the rush for prediction.

Yohe and Dowlatabadi (1999) had earlier offered some pointers on adaptation analysis to climate change under conditions of risk with uncertainty. Autonomous or deliberate adaptation by humans, the authors note, hinges on risk perception, which in turn depends upon welfare valuation. Welfare valuation is based on expectations in the systems about uncertain climate and socioeconomic parameters that change over time with arrival of new information. The risks have to be constantly redefined in terms of newly arriving information and evolving conditions and behavior in the biophysical and socioeconomic systems. Understanding the processing of new information and learning of the participants in an adaptation system is important. The authors point out that social, economic, and political systems can be a source of surprise as much as extremes of natural variability in climate systems and should be monitored along with climate systems. In dealing with uncertainty, all plausible futures need to be considered, including low probability high impact scenarios.

Communicating uncertainty in adaptation analysis is also important. Moss and Schneider's (2000) paper on communicating uncertainty for the IPCC TAR provides valuable guidance on framing and communicating uncertainty. They recommend usage of terms like “likely, unlikely, possible, and probable” to indicate the degree of confidence of the experts on their scientific findings or beliefs. AR4 states likelihood (based on quantitative analysis or elicitation of expert views) of a well-defined outcome in seven categories ranging from “Virtually certain” (< 99% probability of occurrence) to

“Exceptionally unlikely” (<1 % probability). Communicating uncertainty helps to inform decision makers in identifying futures that are most likely and relevant for them.

A few key suggestions emerge for treating uncertainty in adaptation analysis. One, consistent portraits of what the future might bring need to be developed to systematically deal with uncertainty. The second suggestion is to identify adaptation decisions that are robust across (1) many plausible future scenarios, and (2) many ways of modeling the same uncertainty. As a way of finding robust strategies under uncertainty, (Dessai and Hulme, 2007) developed an assessment framework that allows the identification of adaptation strategies that are robust (insensitive) to climate change uncertainties in context of a case study of water resources management in the East of England. They use local sensitivity (one-at-a time experiment) analysis to determine the extent to which adaptation decisions are sensitive to uncertainties in the model parameters-adaptation decisions were found sensitive to uncertainties in regional climate response, aerosol forcing, and green house gas emissions. The research raises questions about how much certainty is required in climate change projections to justify investment in adaptation decisions, and the required certainty can ever be delivered. The third suggestion is to design adaptation decisions such that the decisions can be sequentially implemented. This allows for evaluating and modifying decisions in successive periods in accordance with newly arriving information.

This section ends with a summary of the main lessons (and research needs) drawn from the brief literature overview for adaptation policy analysis. Adaptation analysis will need to consider both climate change and climate variability. However understanding these changes is contingent on having access to reliable regional climate data, which can become an issue depending on how fine a spatial scale we are focusing on. Even with access to good data, it may be difficult to distinguish change from natural climate variability. In addition, existing climate models are applicable at the global scale of analysis.   Downscaling of the climate models to regional levels presents many issues that are yet to be resolved thereby hampering the predictability of the climate models at the regional level. The way out is to consider many future climate scenarios, including the apparently implausible ones. Existing adaptive capacity or coping ranges must be assessed so that thresholds can be identified; region based vulnerability assessments are needed. The climate system has to be studied in combination with the evolution of the socio economic systems. The latter systems can also be source of surprises and future scenarios for them have to be constructed accordingly. Planned adaptation analysis has to consider autonomous adaptation that arises in the system in response to the climatic stimulus, which is a difficulty as human reflexive behavior is largely intractable. In spite of its insufficiencies, the climate system is perhaps the best-studied system relative to the human or biological systems. Understanding is minimal in the context of ecosystem adaptation and biodiversity management, both of which face the highest risk from climate change. There is a dearth of information that needs to be addressed and not all missing information is related to climate (As we will find in the SAV analysis of Essay 2, the information that was most lacking related to the value of the natural resource, and not climate change induced sea level rise). Information gaps like this can hamper the precision of decision analysis.

There are multiple sources of uncertainty that must be addressed and accounted for, with reflexive uncertainty being a challenge to model. Adaptation policy must concentrate on identifying options that are robust under a wide range of climate and socioeconomic scenarios. An approach (in view of what has been learned so far in this essay) would be to model adaptation within the paradigm of risk assessment, and to enhance the analysis by incorporating uncertainty analysis. In risk assessment, available information is collected and utilized to make decisions regarding the risk associated with a particular stressor such as climate change and its biophysical impacts. Decisions in risk assessment are typically not crystal clear and hence there is uncertainty. Uncertainty analysis can be thought of as the part of risk assessment that focuses on the uncertainties in the assessment. Important components of uncertainty analysis include qualitative analysis that identifies the uncertainties, quantitative analysis of the effects of the uncertainties on the decision process, and communication of the uncertainty. The choice of qualitative or quantitative analysis depends on the level of resolution required and the amount of information available. The analyses can range from simple descriptive procedures to quantitative estimation of uncertainty, to more formal decision-based procedures. The assessment of uncertainty combines the view of uncertainty of both the scientist and the risk manager. A good overview of techniques and methods in uncertainty analysis can be found in (Smith, 2006).

1.5. Timing of Adaptation Measures

In this section we investigate the question of optimal timing of adaptation policy and actions under uncertainty. The objective here is to identify, based on the preceding literature reviews and beyond, the key elements that determine the timing of adaptation measures and also their direction of influence on the timing. It is emphasized that the scope of this section is not to determine 'the' optimal timing of adaptation measures, but to enhance understanding of the key elements, and why they need to be considered in the decision making framework for timing of adaptation policies. Wherever relevant, the section also includes thoughts on how adaptation research can be pursued to improve the understanding of uncertainty and policy timing.

1.5.1 Uncertainty and Irreversibility

The importance of uncertainty and the way it interacts with irreversibility to influence policy magnitude and timing decisions was emphasized in the economic literature. Those deliberations are not repeated here. Instead the focus here is on understanding what can be imported from the preceding reviews into the study of timing of adaptation measures, to examine how some of the key features of studies cited could (or not) apply to adaptation problems. Adaptation measures are varied and are not necessarily characterized by all kind of uncertainties and irreversibilities. I identify adaptation examples, where one or more of the issues of uncertainty and irreversibility is a problem, and then examine the question of timing in context of the example.

Almost all studies cited in the economic literature review only consider a one time policy adoption that once adopted imposes sunk cost throughout the time horizon under consideration-it does not allow for policy reversibility. It is reasonable to assume that most adaptation measure will entail a cost- whether it is completely sunk or partially recoverable will depend on the specifics of the problem. For example, adaptation investments in dams for water storage will probably incur irreversible sunk costs, but adaptation investments in air conditioners for warmer climate could constitute a reversible investment if it allowed for the possibility of successful selling of the conditioners if the resulting climate turned out to be not so warm. The mitigation studies established that in the absence of ecological irreversibility, the economic irreversibility will delay the adoption of the policy-particularly so, if there is a possibility of learning and uncertainty reduction over time. These studies are rigid in the sense that they do not allow for the possibility of any degree of reversibility in the sunk economic costs. What happens when the policy costs are not completely sunk and there is a possibility of reversing the costs is yet to be formally explored-intuitively, it would seen that adaptation timing will be less delayed compared to the case of completely sunk costs and the extent to which that will happen will depend upon the degree of reversibility within the time frame under consideration.

The mitigation studies also do not allow for the possibility of the policy to be implemented in an incremental basis. In adaptation, it is possible to conceive of situations where the policy can be implemented on an incremental basis rather than a one-time policy adoption, rather than converting all agricultural production into climate change resistant variety, one could potentially convert one crop at a time or convert incremental areas of land to drought resistant crops at a time. Incremental policy adoption does provide a way for minimizing the scope of 'regret' if uncertainty resolution results in outcomes that differs from likelihood estimations of the outcomes.

Within the context of adaptation, environmental irreversibility characterizes a limited set of problem like biodiversity conservation and ecological restoration.

Adaptation measure here consists of preserving ecological corridors and future habitats so that species can effectively relocate to habitats that are more conducive to their survival. Protecting wetlands and ecological corridors entail huge sunk costs (economic irreversibility), but not doing so allows for the possibility of these lands to be developed. Once that happens, it cannot be undone to revert back to wetlands or corridors- In there lies an ecological or environmental irreversibility. Viewed exclusively without cost consideration, the environmental or ecological irreversibility results in earlier adoption of policies targeted towards protecting environmentally risky lands. When sunk cost considerations are brought into the picture, they work to delay the timing relative to the timing in the case characterized by environmental irreversibility alone. The resultant timing in a case characterized by both irreversibilities would depend upon the net effect of the two opposing forces. Evaluating the net effect requires filtering through the gamut of problems involving uncertainty in the benefits and the costs of protection and discount rate that was pointed out in (Pindyck, 2007).

1.5.2 Catastrophic Events

Adaptation measure could be directed at mitigating the impacts of catastrophic or extreme events e.g., moving coastal settlements to high lands as an adaptation to extreme sea level rise following glacier melting or to cyclones. Of course, one could argue that catastrophes and adaptation should not be even considered together as catastrophes by definition is something that reduces welfare effectively to zero and the effect of any adaptation can only be minor in modifying that outcome. The question would still be relevant for extreme events. The few studies that did consider the possibility of catastrophic impacts of GHG accumulations (in context of mitigation) find that the presence of catastrophic events can lead to earlier and more stringent abatement policies, but only if (1) the likelihood of the catastrophe (the hazard rate) increases sufficiently with the stock of the pollutant (Clarke and Reed, 1994) or (2) if we assume that there is a critical level of stock accumulation at which catastrophic event is triggered and that level is unknown (Tsur and Zemel, 1996). Where does this leave us with understanding the timing of adaptive measures to catastrophic event (and extreme events)? There is no clear answer. Adaptation by definition does not affect the likelihood of these events, but modifies the impacts associated with these events. The probability is exogenous to the adaptation system but the consequence can be modified by proactive adaptation. It would be helpful to explore what the inclusion of extreme events implies for the timing of adaptation measures that increase the coping range to extreme events in the following permutation of cases where (1) the magnitude and the evolution of the exogenous likelihood of the extreme event over time is known and the relation ship between adaptation and consequence is known, and (2) the magnitude and the evolution of the exogenous likelihood of the extreme event over time is unknown and so is the relationship between adaptation and consequence. Such an analysis will help to show which of the uncertainties (on the likelihood side or the consequence side) affects the timing of the adaptation decisions most, and would indicate where efforts should be expended for strategic uncertainty reduction.

A greater risk of catastrophic events will induce early adaptation implementation. Adaptation to catastrophic risks entails a lot of efforts that have to be implemented much prior to the occurrence of the event. Catastrophic climatic scenarios are extreme scenarios among many plausible future climate scenarios. Taking some precautionary adaptive measures help in reducing the variance in the outcome associated with catastrophic events. Including more scenarios of catastrophic risks in adaptation analysis can be insightful for understanding adaptation-timing issues.

1.5.3 Adjustment Costs

The aspect, that has never been explored in context of GHG abatement policies, but which is very relevant for adaptation problems is the concept of adjustment costs. Adjustment costs, as understood conventionally in economics, are a real issue with respect to adaptation to climate change and can exert enormous influence on the timing of adaptation. Identified and much researched in investment theory, adjustment costs usually arise in context of fixed capital. When relative price changes occur unexpectedly requiring firms to respond with quantity changes in production, the optimal amount of quasi-fixed factors like capital for a firm changes unexpectedly necessitating adjustments in the capital stock. Depending on the nature of the capital under question, investment (the rate of change in the capital stock) can be instantaneous or protracted; i.e., the change can occur all at once or be spaced out across longer time periods. Costs can be linear, increasing (convex), or decreasing (concave) in the investment. So the total cost of capital adjustment has two components - (1) the cost incurred in the purchase (or disposal of the capital) and (2) the (transitory) costs that arise because of the pace of capital stock adjustment. Collectively, these costs are known as adjustment costs. Slower the adjustments need to be made, lower is the adjustment costs.

Adaptation to climate change will in any cases require major adjustments in infrastructure and other fixed capital e.g., in coastal communities, with rising sea level, buildings along the coast will have to be abandoned and built elsewhere. Dams need to be built to adjust to changed precipitation or to manage water resources under new climate. High adjustment costs will be incurred for these changes and the costs will be proportional to the pace at which the adjustments have to be made. Adjustment costs, whenever they exist, argue for early implementation of adaptive responses, because early adaptation will result in less expensive protracted adjustments. (Quiggin and Horowitz, 2003) argue that the costs of climate change are primarily adjustment costs-climate change reduces welfare if it occurs more rapidly than the rate at which existing capital stocks, including natural resource stocks, naturally adjusts through market processes. They argue that the costs are not that affected by the amount of change as much as the rate of change. The rate of change (and beliefs about it) is of crucial importance in deciding on the timing of adaptation options.

Fisher and Rubio (1997), mentioned earlier, had looked at the implications of increased climate variability and asymmetric adjustments costs for investments in water reserve. Under the assumption that the benefit function for water withdrawal is convex, the authors find that existence of asymmetric linear adjustment costs along with increased uncertainty (modeled through changes in the variance of water resources) results in a range of inaction for investment in water. Under linear adjustment costs, the authors had found that increases in the variances of water resources had warranted greater increases in the long run water storage capacity. Introducing asymmetric adjustment costs makes optimal water storage capacity less sensitive to changes in variances, but increases the range of inaction for investing in the water resource infrastructure. (Fisher and Rubio, 1997) approach focuses on the first component of adjustment cost stated above-the asymmetry in the cost of purchase and disposal of the capital. Costlier the disinvestments, greater are the range of inaction that this essay as interpret as delay in timing.

1.5.4 Risk Attitudes

The fact that we are dealing with uncertainty forces us to deal with expectations in the system. These expectations are in turn related to risk perceptions of the system's agents or the decision makers and will therefore be closely tied to their attitudes about risk aversion. A climate risk- adverse agent will be keener on early adaptation than a risk-lover agent. For there to be an incentive for society to invest in adaptation, society must be risk averse and the anticipated damages must be large. The Arrow Lind Theorem tells us that society is usually risk neutral to public actions even if individuals in it can be risk averse as such actions are a minor part of society's assets (Arrow and Lind, 1970), but it is only valid within the assumptions of the theorem. The risk attitude at the aggregate levels of decision-making plays an important role in adaptation adoption and can influence timing. Recent efforts have started looking at the different physiological dimensions of uncertainty in climate change perception and communications (Patt, 2007; Marx et al., 2007). These works, consistent with behavioral economic models in which framing matters and in which people do not optimize based on objective probability estimates, help to inform better ways of framing the uncertainty in the decision problems as well as communicating the uncertainty.

1.5.5 Technology

Another element that can affect the timing of adaptation policies but is often neglected in adaptation research is the aspect of technology and its evolution.

Technology affects adaptation either by generating further adaptation options or by influencing the costs of adaptation. If technological evolution holds the promise of delivering better adaptation options in the future, then there is a benefit of waiting to see if less costly adaptation options will become available. The higher the probability of innovation resulting in better adaptation options, more is the incentive to wait. In the ski industry example, better snow making technology could reduce vulnerability (beyond adapting by extending snow making capacity based on current technology). Whether such technology can be created at cost effective ways remains uncertain. Higher the probability of successful innovation in low cost efficient snow making technology, greater is the incentive to wait on any investment in the current technology. The possibility of newer technologies coming into existence that can act as substitute for an adaptation will always delay the adaptation.

1.5.6 Auxiliary Benefits

Many regional impacts assessments find that impacts from climate change look like poor choices from land use. Then adaptation actions taken purely for climate reason would have co-benefits on quality of life even if climate did not change. Including non-climate related co-benefits in the adaptation decision analysis provides an added incentive to adapting early. Similarly, adaptation options that are designed primarily for future climate but which yield benefits under current climate should be readily adopted.

1.5.7 Direction of Influence of Key Elements Combined

When multiple elements characterize the problem, the timing of adaptation measures will depend on the net influence of the elements combined together. Table 1-1 lists the key elements and their individual influence on the timing of adaptation measures adoption. In evaluating when to adapt, careful consideration has to be given to set of the elements that characterize adaptation problem. How important these elements are in influencing the timing of adaptation in a particular problem and how well one can quantify the relative importance of the elements depends on the specifics of the problem. Decision makers should carefully evaluate the relative importance of each of the elements with respect to one another. If a thorough quantitative analysis is not possible, then qualitative analysis should be employed (like multi criteria analysis) to weigh in on the timing issue. Careful consideration of the characteristic elements will at least help the decision maker to judge how important is the issue of timing for his or her problem.

Table 1-1: Key elements and their influence on timing

Element	**Qualification/Type**	**Timing of adoption**
Uncertainty	With learning	Delayed
	Without learning	Early
Irreversibility	Economic	Delayed
	Environment	Early
Adjustment costs	High	Early
	Low/negligible	Delayed
Catastrophic effect		Early
Risk attitudes	Averse	Early
	Lover	Delayed
Technological innovation		Delayed
Auxiliary benefits		Early

The good thing about many adaptation decisions is that it is not a ‘now or a never’ decision. In each adaptation decision period, the decision maker decides on a course of action (or inaction). In the successive period, he can evaluate his decision taken in the previous period in the light of the information and realizations in the second period. If evidence in the successive period indicates that the decision of the earlier period is sub optimal, then adjustments can be made in the successive period to modify the mistake. In this way, the performance of adaptation policies implemented can be evaluated in successive periods. The sequential approach allows disbanding of policies that are found in successive times to be ill suited to the adaptation problem. Adaptation measures need not be implemented all at once but in stages. The ability of not having to implement the adaptation policy all at once but in incremental doses with the opportunity of undoing incorrect current actions enables confident decision-making.

1.6. Conclusion

From the first generation adaptation studies that sough to inform impact assessment to the second-generation adaptation studies that investigated research needs for informing adaptation policy, adaptation research has come a long way. Unfortunately, as noted in AR4, a clear picture of adaptation's potential, limitation, or costs is still not available and existing literature does not indicate how effective various adaptation options are at reducing climate risks, especially at higher levels of warming and related impacts. A major reason for this is uncertainty surrounding the climate change.

Uncertainty is a complicated topic that is being increasingly addressed in the environmental, specifically climate change literature. The usual complications arise with our lack of understanding of the costs and benefits of an environmental policy, appropriate discount rate to use, and when there are opposing economic and ecological irreversibilities characterizing the system under consideration. The consensus from the environmental economic literature is that under uncertainty, any move that is irreversible will be delayed whenever there is a possibility of learning and reducing the uncertainty in the successive periods. With respect to climate change, almost all studies that have looked at the impact of uncertainty have concluded that mitigation activities be delayed because learning (and adaptation) will weaken the environmental irreversibility aspect of the problem. The studies have consistently considered (1) one time reduction, (2) no adjustment costs, and (3) no possibility of increased extreme events or catastrophic investments all within the same framework. Undoubtedly, more research is needed with respect to uncertainty in climate change and alternative modeling of the uncertainties and irreversibilities incorporating the elements not considered before could advance our understanding of the subject matter better.

In dealing with planned adaptation, irrespective of whether it is adaptation that enhances the coping range or adaptation beyond the capabilities of the coping range, the best approach is to begin with an understanding of the baseline vulnerabilities. Impact assessments (that incorporates carefully examined adaptation that would naturally occur in the system) and scenario analysis (that adequately address the human reflexive component of adaptation) should be combined in meaningful ways to generate the relevant vulnerability management framework for policy. This is an integrated risk assessment- management approach where the climate risks and adaptations are considered simultaneously rather than risks being assessed first and then exploring risk management options with adaptation. Risk analysis is subject to uncertainty, and sensitivity analyses (and other techniques of uncertainty analysis) will help establish the impact of the uncertainties on the vulnerability assessments and also help to identify adaptations that are robust to the uncertainties. Once the role of the uncertainties in the decision framework is understood, the aspect of timing of the robust decisions can be addressed based on the key elements identified in this essay.

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ESSAY 2

OPTIMAL STRATEGIES FOR ECOLOGICAL RESTORATION UNDER CLIMATE CHANGE

2.1 Introduction

Projected climate change is expected to pose significant threats to ecosystems and biodiversity in this century. Climate change will affect fundamental ecological processes and the geographic distribution of biotic conditions that impact species survival (Malcolm and Pitelka, 2000; LeRoy Poff et al., 2002). Impacted species will adapt autonomously and try to relocate to areas more conducive to their survival. The successful survival of species will depend critically on the availability of migration corridors and emergence of habitats more suitable to the changing climate. Thus a crucial issue in facilitating ecosystem adaptation to climate change is choosing designs for current resource management programs that maximize opportunities of successful autonomous adaptation of species.

The fact that climate change impacts the distribution of species has spatial implications for ecosystem management in general and conservation and restoration policy analysis and design in particular. Site-specific biotic conditions affect species ability to reproduce, a crucial determinant of successful restoration, thereby making restoration costs site-specific. The return to investment in conservation and restoration effort is therefore affected by the choice of site. Climate change brings forth the possibility that current restoration sites may become unsuitable habitat for the restored species in the future and more suitable habitats may emerge elsewhere. The uncertainty surrounding climate change translates into uncertainty about the location of the ideal habitat sites for species restoration. The spatial uncertainty emerges as a key challenge in site selection in restoration programs.

Anticipating the spatial implications of climate change in the design of restoration programs is important for two reasons. Firstly, restoration has emerged as an important and widely promoted environmental practice in aiding recovery of damaged habitats, wetlands, watersheds, and estuaries. The fact that the USEPA's Office of Water lists about 188 terrestrial and aquatic restoration projects just for the Mid Atlantic Integrated Assessment (MAIA) Region indicates how intensely restoration is practiced.

Secondly, and more importantly, ecological restoration projects can be very expensive. For example, the full costs of restoring an hectare of sea grass is estimated at $940000 in 1996 dollars (Fonseca et al., 2001) while that of per acre of salt marsh restoration costs can range anywhere between $900 to $90,000 in 1997 dollars (Louis Beger Associates, 1997). In addition, restoration costs are sunk costs for society- once invested the expense cannot be recovered. Stressors like climate change, if unaccounted in program design, may result in unnecessary expenses undermining the effectiveness of the program. Failure to anticipate the impacts of climate change may result in failed restoration programs.

There is limited research that addresses the economic consequences of the impact of climate change on site selection in resource conservation and restoration program designs. Although, a few recent papers do address spatial aspects of conservation programs in general when allocating conservation funds (Wu and Boggess, 1999; Wu and

Skelton-Groth, 2002), work that explicitly addresses the economic implications of climate change for site selection in conservation and restoration programs is rare.

This essay examines the effect of climate change on the design of optimal strategies for habitat restoration under climate change in an aquatic environment using the lower Chesapeake Bay's Submerged Aquatic Vegetation (SAV) restoration program as a case study. The concern with climate change is that it will result in magnified sea level rise beyond what would have naturally occurred. The essay develops a methodological framework that determines the optimal extent of SAV restoration at select sites under climate change induced sea level rise that takes into account SAV dynamics, the benefits and costs of restoration, and uncertainties about climate change. By jointly addressing the key issues of (1) uncertainty regarding the impacts of climate change at local scales and (2) policy irreversibility associated with the sunk costs of restoration efforts, the essay offers a first of its kind study in analyzing the spatial implications of future climate change for ecological restoration projects.

Connecting climate change to ecological restoration is important to offer appropriate guidance to authorities tasked with environmental restoration duties. Guidance is extremely relevant for those in charge of restoring species that will be greatly impacted by climate change. This is especially true in context of marine species as they are limited in their ability to adapt. Understanding the implications of climate change for restoration policy design also contributes to the understanding of the broader problem of ecosystem adaptation to climate change.

2.2 Climate Change and SAV Restoration Program

2.2.1 *SAV Restoration Program in the Chesapeake Bay*

The term Submerged Aquatic Vegetation (SAV) broadly refers to a diverse community of underwater sea grasses that grows in the shallow subtidal or intertidial zones. There are approximately sixty species of sea grasses known worldwide. Growing mostly in the unconsolidated sediments, they perform the important function of binding millions of acres of shallow water sediments in the coastal waters with their roots and rhizomes while simultaneously curbing waves and currents with their leaf canopy. The leaf canopy also curbs resuspension of water particles and also traps water column nutrients too. The water cleansing effect is further enhanced due to the nutrient uptake by sea grass blades and roots-dissolved nutrients are assimilated in the plant biomass, improving water quality The physical stability, reduced mixing of water particles, and the shelter services that SAV provides is the basis of highly productive ecosystems. The importance of sea grasses in coastal ecosystems is well documented and the nature of their general function and resource value is no longer contested (Fonseca et al., 1998).

SAV is essential for the aquatic environment of the Chesapeake Bay. Seventeen species of submerged aquatic vegetation are commonly found in Chesapeake Bay and its tributaries. *Zostera marina* and *R. maritima* are the dominant SAV species found in the Delmarva Peninsula coastal bays. *Zostera marina* (eelgrass), the only "true" seagrass species, can tolerate salinities as low as 10 ppt, and is dominant in the lower reaches of the bay. In the Chesapeake Bay, SAV provides food, protection and nursery habitat for a broad range of aquatic organisms, contribute to the oxygenation of the water and prevent shoreline erosion and sedimentation. The habitat services of SAV are highly valued for the fish and shellfish population, chief among which are striped bass and the blue crab, an integral part of life and culture of the Chesapeake Bay. SAV also contributes to improving the Bay water quality by removing the excess nutrients from water that can cause unwanted algal growth. Water quality is a huge concern in the Chesapeake Bay (the Chesapeake Bay, which is on the Environmental Protection Agency's (EPA) 'impaired waters' list, is plagued with nitrogen and phosphorous pollution), and the water quality improving services of the SAV is highly valued in the Bay.

SAV abundance in the Chesapeake Bay regions once exceeded 200,000 acres but aerial surveys conducted by Virginia Marine Resources Commission in 1978 documented only 41,000 acres (Moore and Orth, 1997). As for many other resources of the bay, excessive nutrients and sediment loads are held primarily responsible for the SAV decline. Bay scientists believe that 'resurgence of underwater bay grasses is critical to the overall Bay restoration effort' (Chesapeake Bay Program, 2003). Consequently SAV restoration is a top priority with the Chesapeake Bay Authority and other Bay management agencies.

The Chesapeake Bay Program (CBP) has committed significant resources over the past 20 years to map SAV acreage annually, to determine the causes for the decline in more details, and to identify the best methods for protecting and restoring SAV populations. For 2000, 27,986 hectares (69,126 ac or 279742 thousand sq meters) of SAV were mapped in Chesapeake Bay and its tributaries. Efforts to restore SAV have increased acreage over time but the acreage of restored SAV keeps fluctuating from year to year - e.g. in 2003, a total of 64,709 acres (or 261868 thousand sq meters) of SAV were estimated to be growing in the Bay - a 30 percent decline from the previous year's tally. The greatest obstacle to restoration success has been the poor water quality of the Bay. Restoring underwater Bay grasses relies overwhelmingly on improving water quality. Bay managers have now begun to supplement pollution reduction efforts with experimental aquatic grass plantings.

The fluctuating nature of SAV stocks have resulted in changing SAV restoration targets over time. In the 2000 Chesapeake Bay Agreement, the watershed partners committed themselves to the bold goal of restoring 114,000 acres (461341632 sq meters) of SAV with an idea of revising the goals and strategies for accelerating SAV restoration in 2002 (Chesapeake Bay Program Agreement, 2003). Commensurate with that, in 2003, the CBP adopted a goal and strategy to accelerate SAV protection and restoration. The goal is to achieve 185,000 acres (748668438. sq meters) of SAV (through both restoration and natural growth), baywide, by the year 2010. The strategy to achieve this goal is based on consensus among the formal and informal partners of the CBP, and its status will be reported annually and reevaluated in 2008 (Chesapeake Bay Program, Bay Trends and Indicators, 2007). Inclusive in the strategy is a commitment to plant 1,000 acres by 2008. In the first two years of their effort, Bay managers have been able to plant only one-tenth of their goal with total SAV acreage tallying to 42 % of the 2010 goal. Large-scale restoration of SAV in Chesapeake Bay is undoubtedly underway and making progress, but still has a long way to if restoration targets are to be made. Both funding for SAV planting, and capacity for doing it, will need to be increased dramatically to meet the goal of 1,000 acres planted by 2008. To date the NOAA Chesapeake Bay Office and the USACE Engineer Research and Development Center

(ERDC) have funded almost all of the large-scale planting, and neither agency has been able to increase funds to meet the annual need.

2.2.2. *Potential Impacts of Climate Change on the SAV Restoration Program*

To understand how climate change can impact SAV restoration, it is important to understand the habitat factors that influence SAV growth in general. The habitat factors deemed critical for successful SAV restoration are (1) water temperature, (2) light penetration, (3) water currents and wave action, (4) bottom sediment, and (5) water depth (range: below low tide line to about 2 meters in depth) (Chesapeake Bay Program, Preserving and Restoring Bay Grasses, 2004). The factors are not independent of one another and interact with one another to affect the resurgence of SAV. Light is by far the most important factor affecting bay grass growth. Without light, SAV cannot perform photosynthesis and create the required energy to grow. Water clarity and depth, together, matter in determining the amount of light reaching the underwater SAV. Water quality in turn is affected by sediments (Total Suspended Solids), algae and epiphytes, and nutrients like dissolved inorganic nitrogen and dissolved inorganic phosphorous. Sediments (often resulting from sea bottom scouring by heavy wave activity) decrease light penetration by trapping light and nutrients promote excessive growth of algae blocking necessary light. Water depth affects light penetration by increasing the column of water that light must travel through to reach the SAV (Chesapeake Bay Program, 2004).

Climate change impacts on SAV will likely include effects from (1) increased water temperature, (2) increased carbon dioxide in sea water, (3) Increased frequency and intensity of high energy storms, and (4) Sea level rise (USGS FS-090-97, 1997; Short and

Neckles, 1999). Increased water temperature would reduce productivity and cause dieback of SAV growing in regions already in the upper limit of their thermal tolerance. Increased temperatures may also combine with nutrient pollution to further enhance the growth of competitive algae (i.e., seaweed and phytoplankton); an increase in algal production can lead to reductions in the sunlight that seagrass require for survival.

Increased atmospheric carbon dioxide causes an increase in the dissolved carbon dioxide concentration in seawater. This will enhance photosynthesis in many types of seagrasses but likely at the expense of those species with a reduced carbon-extraction capacity. This is expected to lead to shifts in species distributions. Increased CO_2 levels may also benefit the algae attached to seagrasses; increased algal growth would restrict light levels (i.e., by shading plant leaves) and thus lead to seagrass decline. Storms can uproot plants, reduce water clarity, or redistribute sediments such that seagrass meadows are smothered. Increases in rainfall and river water discharge would also increase sediment loading to the water column reducing required light levels.

Climate change induced sea level rise may increase the water depth at the Bay restoration sites, reducing the light needed for successful SAV growth. Changes in tidal dynamics (e.g. water current speed, tidal range) accompanying sea level rise could have a range of impacts including reduction in light, increased depth for plants at low tide, and an increase in water column turbidity. The increase in upriver penetration of salt water and increases in salinity levels and pulses within estuaries (i.e., salinity intrusion) is also to be expected with a rising sea level. Sea grasses require specific salinities for reproduction and propagation; shifting salinity regimes would limit the reproduction and distribution of some sea grass species yet favor those that are more salt-tolerant. As well, increased salinities are associated with an increase prevalence of 'wasting disease', a highly destructive disease currently impacting eelgrass meadows in some U.S. coastal areas.

The fact that SAV communities are susceptible to long-term environmental changes predicted to accompany climate change is well established. However, the enormous complexities inherent in climate change and its effects on species and ecosystems have led many scientists to conclude that impacts of the environmental changes accompanying climate change can be understood only after significant warming has occurred, by which time it might be too late for recovering sea grasses. A complete understanding of the effect of climate change on SAV would have to be founded on understanding the individual impacts (physical, biological, and social) of the interrelated factors through which climate change will manifest itself. In this analysis we investigate the impact of climate change induced sea level rise on the design of the SAV restoration program in the Bay. All other factors, including water quality and temperature, are assumed to be at their current level and are held constant throughout the analysis.

2.2.3 Case Study: Area and Decision Problem under Climate Change

The case study area is located in Hampton Roads, Virginia. It lies in the lower bay zone, inset in figure 2-1. The Chesapeake Bay Authority, working in collaboration with many state and local agencies, supervises and monitors the SAV restoration program across the Bay. Within the Hampton Roads area of Virginia, the case study site, it is the Virginia Marine Resource Commission that is tasked with SAV restoration. Figure 2-1 shows the case study area, with the red areas on the map indicating existing SAV (11,792 acres or 47720530 sq meters) as of 2001. Existing SAV acreage (based on 2001 inventory) for the case study site is about 57 % of historically known acreage (20,706 acres or 83794209 sq meters) (Virginia Institute of marine Science, 2004). The SAV in this lower Bay region is predominantly eelgrass (Zostera Marina), occurring at water depths of 0.5 to 3 meters along the coast.

Figure 2-2 illustrates how changing sea level results in SAV relocating to shallower depth. In the figure, C indicates current sea level while F indicates future sea level. When the sea level is C, SAV grows in region A. When the sea level rises to F, SAV relocate to region B where the water depth is suitable. Post sea level rise, 'ideal' SAV growing region, and thereby, the restoration sites will emerge in relatively shallower waters. The productivity of current SAV growing regions located in the deeper waters decreases as the water depth increases and light penetration diminishes. SAV migrates to sites in shallow waters where the depth criterion is satisfied.

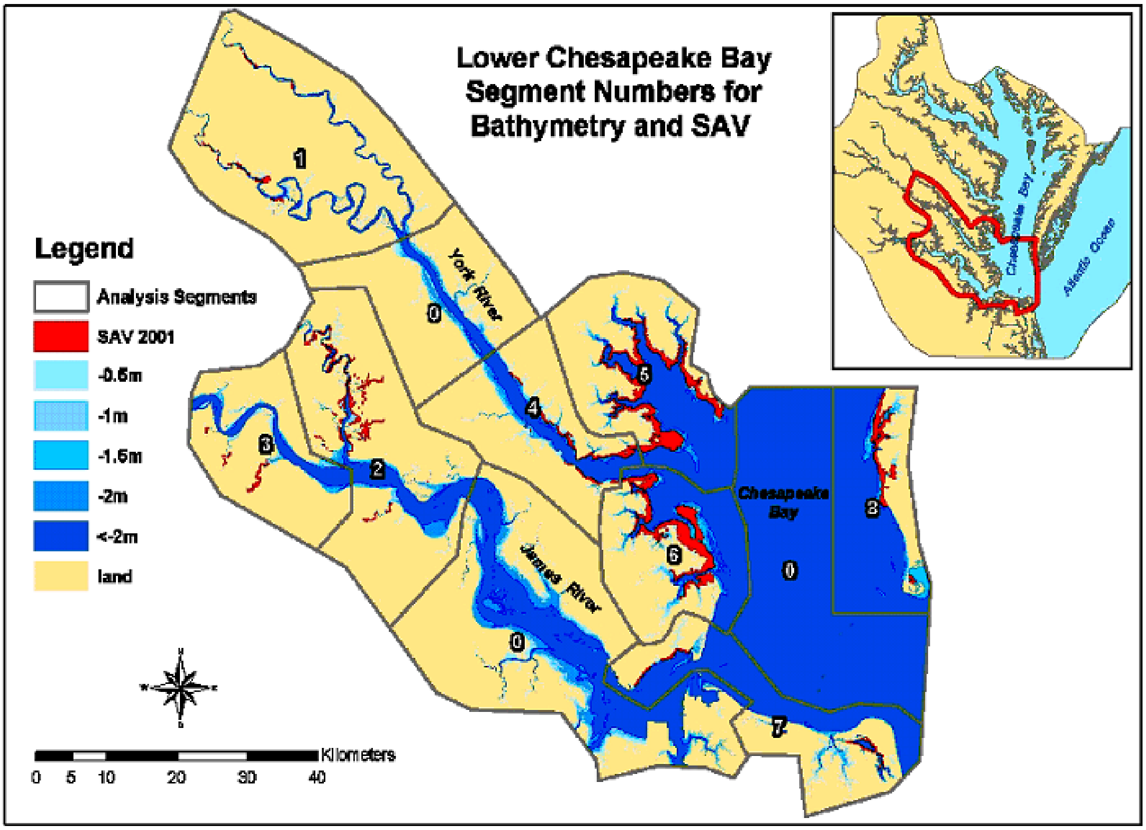

Figure 2-1: Map of the case study site-Hampton Roads, South East Virginia. Red areas on the map indicate 2001 SAV presence

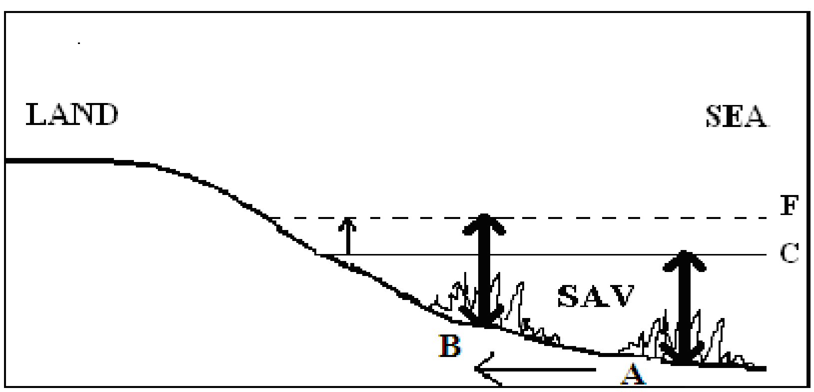

Figure 2-2: Effect of changing water depth on SAV location

The SAV dynamics in this analysis at a given restoration site is driven solely by changes in water depth at the site resulting from climate induced sea level rise. Therefore, to facilitate the understanding of the depth changes that occur with sea level rise at the historic SAV sites, it is necessary to categorize the restoration sites in terms of their water depth. The essay consequently develops the notion of depth zones (or depth bands). Each depth zone represents areas of Bay that are of uniform depth. The area of historic SAV beds within the case study area is divided into 5 depth zones corresponding to current depths of 0.5, 1, 1.5, 2, and 2.5 meters. All existing SAV beds and areas of historic SAV sites are located in one of the five depth zones. Assuming that SAV can only be restored in historic areas, the maximum area available for restoration (restoration region for that depth band) in any depth zone is the sum total of the areas of the historic SAV sites located within that depth zone. A closer look at the area distribution of existing and historic SAV across the depth bands indicates that shallower depths have more of the historic SAV and existing SAV in them compared to the bands with greater depths. This is illustrated in Figure 2-3. The maximum abundance of SAV in the Chesapeake Bay in general (and in the case study area) typically occurs at 0.5 meters (19.69 inches) water depth.

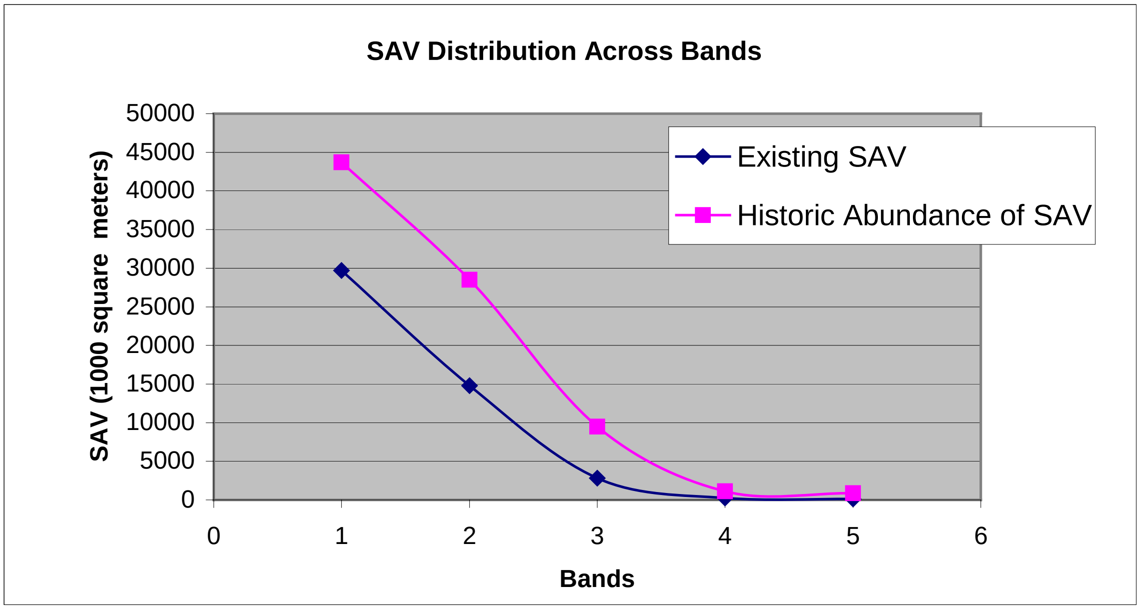

Figure 2-3: Distribution of Existing and Historic abundance of SAV across the depth bands

With rising sea level, the shoreline moves inland. Although SAV can migrate from deeper to shallower waters in the sea, it has restricted opportunities of moving inland, as it cannot grow on land. There exists some possibility that SAV can grow in the tidal marshes along the coast. The tidal marshes, on account of their biotic similarity with SAV habitat, have the potential to become SAV sites. SAV can successfully migrate into the tidal marshes once it becomes sub aqueous under the rising sea.

The potential loss of SAV at their current deep water sites and the potential of successful migration into the tidal marshlands, both in response to sea level rise, have implications for SAV restoration program in the lower Bay area. Consideration of climate change brings the possibility that SAV restored at the historic SAV sites located in the deeper waters could be lost to sea level rise in the future. Restoration entails sunk costs-it constitutes an irreversible investment for society. If the deep water historic sites were to be restored and then the restored SAV were to be quickly lost to future sea level rise before the benefits of restoration could accrue, it would imply a situation where the costs of restoration is incurred but the source of the benefits is eliminated before the benefits of restoration could be obtained. Restoration would, in that case, be a poor investment choice. The fact that existing SAV at 0.5 meters depth can naturally relocate to the tidal marshlands in case the sea level rises provides an additional argument in favor of not investing in restoration at deep water historic SAV. But if current benefits from SAV restoration were high it would merit restoration even if the restored SAV were to be lost in the future. This is because, even if restored SAV were to be lost in the far future, there are benefits of restoration that could be potentially obtained from the restored SAV in the present and near future. Not undertaking restoration would imply foregoing those benefits. The immediate benefits that can be gained currently could be far larger than the cost of restorations justifying restoration at all historic SAV sites even if the restored SAV in the deep water sites were to be lost to sea level rise in the future. The decision of whether to restore the deep water sites or not therefore depends on (1) the time path of restoration and restoration benefits (accruing out of the act of restoration) versus (2) sea level rise and destruction of the SAV (accruing out of the sea level rise). The time paths of restoration, restoration benefits, and sea level rise emerge as the key elements in the restoration decision.

The uncertainty regarding climate change induced sea level rise prevent the decision makers from knowing exactly how sea level rise will occur or what its impacts will be on restored SAV. Although the Bay Program considers restoration as a urgent requirement, it is truly not exclusively an immediate choice - the decision maker does have the option of not restoring immediately but waiting for more information to arrive that can dispel the uncertainty surrounding climate change. Waiting does entail the opportunity costs of foregoing the benefits that could have been obtained in the current period had restoration occurred. However, ignoring the aspect of waiting for new information that could potentially result in better restoration decisions introduces a bias towards immediate restoration in the restoration decision analysis. A failure in anticipating climate change induced sea level rise and in adapting SAV restoration targets at the currently intended restoration sites accordingly will result in inefficient spatial allocation of SAV restoration effort inversely affecting the net benefits of restoration.

Current SAV restoration policy as designed by the Chesapeake Bay program does not account for the impacts of climate change induced sea level rise. Consideration of sea level rise raises the following questions- Does including climate change in the SAV restoration decision analysis call for the same design of restoration (restoring SAV to the known historic SAV abundance in all the five depth bands) as is being pursued under current policy or does it change substantially?' Or does the (1) the potential for greater losses of restored SAV in the deeper waters, and (2) the possibility of gaining SAV in the tidal marshlands, make less restoration at the historic SAV site situated in deeper waters the optimal restoration strategy under climate change? To be able to answer the questions, optimal strategies for SAV restoration need to be determined under climate change. Restoration strategies, in the context of this analysis, entail a portfolio of choices regarding alternative depth bands and the extent of restoration at these bands. The restoration decision problem under climate change, within the context of the case study, is to determine the optimal extent of restoration at the current (historic) SAV sites while accounting for the costs and benefits of SAV restoration, and the uncertainty in sea level rise.

2.3 Objectives and Methodology

The overall objective of this essay is to examine the implications of climate change induced sea level rise for the design of the SAV restoration program in the lower Chesapeake Bay. The specific objective are-:

1. To determine economically optimal strategies for SAV restoration under climate change. Within the context of the case study, this means determining the optimal extent of restoration of the total historic SAV area located in each depth band of the case study area.
2. To account explicitly for the uncertainty surrounding climate change induced sea level rise
3. To deliberate on the costs and benefits of SAV restoration.
4. To derive implications of the resulting analysis for current SAV restoration policy in the Chesapeake Bay.

To achieve the objectives, a dynamic model of SAV restoration is developed in the essay and is analyzed twice - once for the case without climate change (the baseline) and once for the case with climate change. Using alternative scenarios of future climate, the model incorporates uncertainty about climate change. Each climate scenario is defined by a given sea level rise and the associated probability of that sea level rise. The general development of the model and the optimization analysis that determine optimal restoration strategies for SAV restoration is presented in the next section (Section 2.4).

The presentation of the model is then followed with an outline and discussion of the assumptions that are made for empirical implementation of the model in context of the case study (Section 2.5). The results of the optimization analysis for the baseline and climate change and sensitivity analysis (around specifications for probabilities of sea level rise, restoration costs used in the analysis) are reported and discussed in the results section (Section 2.6). The role of the tidal wetlands in SAV restoration is examined in Section 2.7 and the essay concludes, in Section 2.8, with a discussion on current restoration policy reviewed in the light of optimal policy as established by this analysis.

2.4 Model

A dynamic model is created that integrates (1) the relation between restoration strategies (how much of the historic SAV area to restore in each depth zone in each time period) and the stock of SAV successfully restored, (2) the impact of sea level rise on the restored SAV in each period, (3) the costs and benefits of restoration, and (4) the uncertainty of sea level rise- defined by a specified sea level rise and the probabilities associated with that sea level rise. The optimization problem then determines the restoration strategy that maximizes the discounted sum of expected long run net benefits arising from the restored SAV subject to SAV dynamics over the period.

As stated in the case study outline in section 2.2.3, the SAV dynamics is driven exclusively by changes in water depth resulting from sea level rise. To facilitate an analysis based on water depth changes at a site, all restoration sites in the study area is grouped into five depth zones located at current depths of 0.5, 1, 1.5, 2, and 2.5 meters. Let t denote time, (t =0 to T), i denote the sea level rise scenario, and j denote the depth zones in which the sites intended for SAV restoration are located, (j=1, 2, 3, 4, 5). There are (T+1) decision periods in the planning horizon. Each depth zone j has an existing stock of SAV[1], denoted by EXS^j - this is the initial SAV in each depth zone in the beginning of the first decision period 0. Decisions on restoration are made at the beginning of each of the decision period t in the planning horizon. Let r_t^{ij} denote the restoration success ratio at a given depth zone j in period t under climate scenario i ($0 < r_t^{ij} < 1$). r_t^{ij} is the area of SAV that is gained as restored SAV at a restoration site in depth zone j if unit area of SAV restoration is undertaken at this depth, in period t under scenario i. The restoration success ratio is an artifact of the model that is introduced to capture the inherent effect of depth on SAV growth-as stated earlier, SAV thrives better in shallow waters, and the restoration success ratio in the model allows for greater areas of SAV restoration to be established as restored SAV in shallow depth zones relative to deep water zones. The decision (or the control) variable is x_t^{ij}, the area of the historic SAV in depth zone j that is subjected to restoration effort under climate scenario i in period t. It is assumed that at t=0, climate change is unknown, and so restoration choices for period 0 is not scenario contingent i.e. for $t = 0, x_t^{ij} = x_t^j, \forall j$. Sea level rise is assumed to be known in the subsequent periods and hence the restoration choices (x_t^{ij}) in periods t >0, is state contingent. State contingent choices mean that the decision maker gets to observe the resulting sea level rise before he decides on restoration in the depth bands in each period.

[1] The coverage area of SAV is used as a metric for measuring the stock of SAV throughout the analysis. No consideration is taken of the density shoots or of biomass in determining the SAV abundance.

Let α_t^{ij} be the proportion of SAV that is lost in each depth zone j due to sea level rise under climate scenario i, $0 < \alpha_t^{ij} < 1$. The proportion of SAV retained in each depth zone in t, t>0, is given by $(1- \alpha_t^{ij})$. Equation (2.1) gives the evolution of SAV at depth zone j under climate scenario i over time. The stock of SAV at depth zone j under climate scenario i in t+1 will be the stock of total SAV from the previous period t that is not lost to sea level rise.

(2.1) $$S_{t+1}^{ij} = (1-\alpha_t^{ij})(S_t^{ij} + r_t^{ij} x_t^{ij})$$

Let E_t^i denote the area of tidal marshlands in period t that gets submerged under the rising sea and becomes SAV growing areas. The 'emergent stock of SAV' from the tidal marshlands adds to the total SAV stock. Let Δ_t^i be the increment to the emergent SAV stock in the tidal marshes in period t under climate scenario i. Equation (2.2) represents the evolution of the emergent stock of SAV in the tidal marshes over time. It is assumed that there is no SAV migration into the tidal wetlands in period 0, i.e. $E_0=0$.

(2.2) $$E_{t+1}^i = E_t^i + \Delta_t^i$$

Equation (2.3) gives the total stock of SAV (S_t^i) for each period t under scenario i. It is the sum of the SAV in all the depth zones and the emergent stock of SAV from the tidal marshes.

(2.3) $$TS_t^i = \sum_i S_t^{ij} + E^i$$

The climate scenarios (sea level rise and probability) influence the course of r_t^{ij}, Δ_t^i, and α_t^{ij}. Let the terminal stock of SAV that remains at the end of the (n+1)th decision period be denoted by S_T^i.

Benefits of SAV, B_t, accrue in each period and are a function of the total amount of SAV in the relevant period i.e. $B_t = B_t(\sum_j (S_t^{ij} + r_t^{ij} x_t^{ij}) + E_t^i)$. Let *c* denote the constant per unit cost of restoration and ρ_t the discount factor per decision period, which applies over all decision periods and is equal to $\frac{1}{1+\delta}$, where δ is the discount rate. Each scenario of sea level rise occurs with probability p_i.

The optimization problem is to maximize the sum of the stream of expected net benefits of SAV restoration. Mathematically, it is a dynamic optimization problem of form

$$\underset{x_0^i, x_{t,t>0}^{ij}}{\mathrm{Max}} \qquad J = [B(TS_0^i) - \sum_j cx_0^j] + \sum_i p^i [\sum_{t=1}^{T} \rho_t [B(TS_t^i) - \sum_j cx_t^{ij})] + \rho_{T+1} V(TS_{T+1}^i)]$$

Subject to the constraints

(2.1) $\quad S_{t+1}^{ij} = (1 - \alpha_t^{ij})(S_t^{ij} + r_t^{ij} x_t^{ij}) \quad$ for $t \in [0, T]$, i, and j

(2.2) $\quad E_{t+1}^i = E_t^i + \Delta_t^i \quad$ for $t \in [0, T]$, i

(2.3) $\quad TS_t^i = \sum_j (S_t^{ij} + r_t^{ij} x_t^{ij}) + E_t^i \quad$ for all i, j, $t \in [0, T]$

(2.4) $\quad x_t^{ij} \le A_t^{ij}, A_t^{ij} = H^j - S_t^{ij} \quad$ for all i,j, $t \in [1, T]$

(2.5) $\quad x_t^{ij} \ge 0 \quad$ for all *j,i,t*

Initial (First Period) conditions

(2.6) $S_0^j = EXS^j$ for all i

(2.7) $E_0 = 0$

S_t^{ij}, for all j,t,i are the state variable and x_t^{ij} are the control variable. J is the expected present sum of the discounted stream of all period net benefits arising from the restoration of SAV plus the final value of the terminal SAV stock. Equation (2.1) and (2.2) are the transition equations for the system. Equation (2.4) states the constraint that the area to be restored in band j cannot exceed the area available for restoration (A_t^{ij}) in band j. A_t^{ij} is equal to the difference between the historical SAV area (H^j) and the existing SAV (S_t^{ij}) area. Equation (2.5) states non-negativity constraint governing x_t^{ij}, i.e. the choice of restoration area for any period under any climate scenario cannot be less than 0. Equations (2.6) and (2.7) reiterate the initial conditions. The solution to the problem will yield optimal values for $x_0^j, x_t^{ij}, \forall t, i, \text{and} j$.

The expanded Lagrange corresponding to the optimization problem is

$$L = B\,(\sum_j [S_0^j + r_0^{ij} x_0^j]) - \sum_j c x_0^j + \sum_j \lambda_0^j [EXS^j - S_0^j]$$
$$+ \sum_i p_i [\sum_{t=1}^{T} \rho_t [B\,(\sum_j [S_t^{ij} + r_t^{ij} x_t^{ij}] + E_t^i) - c(\sum_j x_t^{ij}) + \sum_i \lambda_{t+1}^{ij}((1-\alpha_t^{ij})(S_t^{ij} + r_t^{ij} x_t^{ij}) - S_{t+1}^{ij})] + \rho_{T+1} V(S_{T+1}^i)$$
$$+ \sum_i \sum_t \Omega_{t+1}^i [E_t^i + \Delta_t^i - E_{t+1}^i] + \sum_i \sum_t \gamma_t^i [TS_t^j - \sum_j (1-\alpha_t^{ij})(S_t^{ij} + r_t^{ij} x_t^{ij}) - E_t^i] + \sum_j \theta_0^j [H^j - EXS^j - x_0^j] +$$
$$\sum_j \sum_i \sum_t \theta_t^{ij} [H^j - x_t^{ij} - S_t^{ij}]$$

where, the LaGrange multiplier or costate variable, λ_t^j. Setting aside the area constraints, the Kuhn Tucker conditions for maximization with respect to the control variables (or the restoration choice variables) of the analysis, x_0^j and x_t^{ij}, are

$$\text{(2.8)} \qquad \frac{\partial L}{\partial x_0^j} = \frac{\partial B}{\partial x_0^j} - c + \lambda_1^{ij}(1-\alpha_0^{ij})r_0^{ij} \le 0, x_0^j \ge 0, \left(\frac{\partial L}{\partial x_0^j}\right)x_0^j = 0, \forall i, j$$

$$\text{(2.9)} \qquad \frac{\partial L}{\partial x_t^{ij}} = p^i \rho_t [\frac{\partial B}{\partial x_t^{ij}} - c + \lambda_{t+1}^{ij}(1-\alpha_t^{ij})r_t^{ij}] \le 0, x_t^{ij} \ge 0, \left(\frac{\partial L}{\partial x_t^{ij}}\right)x_t^{ij} = 0, \forall i, j, t$$

λ_t^j is the contribution which an additional unit of SAV resource would make to the value of SAV benefits at the beginning of the period i.e. it is the shadow value of the stock at time t. In Equation (2.8), $\frac{\partial B}{\partial x_0^j}$ represents the additional current benefit that would accrue from an additional unit of restoration in period t=0. In the same equation, $(1-\alpha_0^{ij})r_0^{ij}$ represents the proportion of successfully restored SAV that survives sea level rise in period t=0. The term $\lambda_1^{ij}(1-\alpha_0^{ij})r_0^{ij}$ represents the present value of the marginal increase in stock of SAV through restoration in period t=0. The Equations (2.8) states that at the optimum, the sum of the current marginal benefit from restoration ($\frac{\partial B}{\partial x_0^j}$) and the future marginal benefit ($\lambda_1^{ij}(1-\alpha_0^{ij})r_0^{ij}$) must equal the marginal cost of restoration i.e. c. Equation (2.9) reiterates the same principal of dynamic optimization in present value terms-it states that the net gains in benefits of restoring a unit of SAV in any time period t under scenario i (i.e. present value of current benefits in that period and the present value of the benefit accruing from the addition to the stock in the next period) should be equal to the present value of costs of restoring that unit of SAV in period t. If the costs outweigh the benefits for all positive values of the control variable, then the optimal decision would be not to restore any amount of SAV.

2.5 Implementation of the model

2.5.1 Restoration Methodology

Fonseca et al. (2001) provide the most comprehensive summary on sea grass restoration and its costs. Fonseca states that if all conditions are met, then it is possible to restore a site within a period of 5 years. The commonly accepted method of restoration is transplantation although direct seeding methods are being increasingly experimented on. Planting of SAV transplants occurs in year 1 and is monitored for a successive period of 3 years including monitoring in the year of the planting. Remedial planting (usually 30% of the original) occurs in year 2 and these are monitored for the next three years. Remedial planting is repeated each time the initial planting fail to survive. On average, 70% of all plantings succeed and grow into restored SAV.

2.5.2 Time Horizon

The SAV restoration problem studied here is a regional adaptation decision problem. Regional decision problems usually have short planning horizons. Climate change, on the other hand, is a long-term problem-the further into the future it is, the more defined and perceptible will the impacts of climate change be. The fact that the SAV restoration program is a regional problem makes it imperative to study the effect of sea level rise on the restored SAV in an immediate context. The earliest year for which sea level rise projections for the Mid Atlantic Region has been determined is the year 2030 (MARA, 2000). Year 2030 is set as the horizon, and the impact of sea level rise on the stock of SAV is explicitly modeled for each time period (t) till 2030. It is recognized that sea level rise would occur beyond 2030, and the likely time horizon for SAV restoration is much longer. The choice of year 2030 is dictated more by pragmatic reasons; the analysis uses a dynamic model with multiple states and shorter time horizon is computationally easy. The choice of the time horizon essentially should be made such that it captures enough of the economics of the model, and the year 2030 is adequate for the purpose of this essay. Sensitivity Analysis will be conducted to evaluate the degree to which the choice of the time horizon influences the results of the analysis.

There are 5 time periods in the model i.e. t=0, 1, 2, 3, 4. Each time period represents a length of five years, the time deemed suitable for a complete round of restoration (Fonseca et al., 2001). The time frame in the model is therefore spans calendar years from 2005 to 2030.

2.5.3 Calibration of the Model Parameters

2.5.3.1. Restoration Success Ratio

As stated earlier, the restoration success ratios are modeled to capture the effect of water depth on SAV restoration. The restoration success ratio therefore depends on the water depth at the site i.e. $r_t^{ij}(d_t^{ij})$. As noted earlier from Figure 2-3, the shallower depth bands have more of the historic SAV and existing SAV in them compared to the bands at greater depths. The variation in SAV acreage across the depth bands is attributed to a difference in water depth. At current distribution of water depth, the existing SAV is a good approximation of the maximum SAV that can be grown in a band if all the previously SAV growing areas within the band were to be restored. The ratio of existing

SAV to previously documented SAV (i.e. Existing SAV/Historically Known Abundance of SAV) at a given depth is used to calibrate initial restoration success ratio at that depth. The restoration success ratio calibrates to 0.679, 0.519, 0.294, 0.236, 0.125 for water depth of 0.5, 1, 1.5, 2, 2.5 meters respectively; these values are treated as the maximum value for restoration success ratio at these depths. Any further increase in water depth in these bands beyond their current depths would inversely affect the value of the restoration success ratio as depth and SAV abundance are inversely related. As the resulting water depth in the depth zones increases over time with increasing sea level, the restoration success ratio for the depth zones in each time period are adjusted proportionately.

2.5.3.2. SAV Loss Rate

SAV typically fails to grow at sites with water depth greater than 3 meters. This implies that for the five depth zones with current depth distributions of 0.5, 1, 1.5, 2, and 2.5 meters, an increase in depth of 2.5, 2, 1.5, 1, and 0.5 meters respectively will increase the depth beyond the tolerable limit of 3 m and will drive the SAV stocks in the bands to 0. Let the increase in depth that will completely eliminate SAV in each band (given the current distribution of depth) be denoted by L^j, L^j corresponds to values of 2.5, 2, 1.5, 1, 0.5 meters for j = 1, 2, 3, 4, and 5..

The cumulative depth increase in the band in each period will depend on the period t under consideration and the underlying sea level rise scenario i.e. $slr_t^i = slr^i * t$. 'slr^i' is the per period increase in sea level under sea level rise scenario i. With incremental sea level rise, the water depth in every period that will completely eliminate the then achieved stock of SAV is given by $L^j - slr_t^i$. The proportion of SAV that is lost in each period is then given by $\frac{slr_t^i}{L^j - slr_t^i}$. This proportion is used as α_t^{ij}, the SAV loss proportion in each period.

2.5.3.3. Wetlands Gain

The portion of the tidal marshlands that becomes sub aqueous (emergent stock of SAV) needs to be determined. In the absence of access to digital elevation data for the study area that could ascertain the precise area of the tidal marshlands that would have become submerged for a given sea level rise, assumptions have to be made about how much tidal marshland become sub aqueous for a given 'slr' unit of sea level rise and proportionately compute the wetlands gain under different scenarios of sea level rise.

Tidal wetlands in Virginia are defined for regulatory purposes using a specific elevation range above mean low water that was developed from empirical evidence back in the late 1960's. The Virginia law states that tidal wetlands include those areas with appropriate vegetation that lie between mean low water and 1.5 times the mean tide range above mean low water. So, one approach to calculating the elevation at which sea level rise would fully inundate existing wetlands is simply to take the mean tide range and calculate 1.5 times that number. The difficulty in this approach lies in the fact that tide ranges vary throughout estuarine systems like the Chesapeake Bay because of the hydrodynamics of wave propagation in enclosed bays. The Chesapeake Bay tide ranges increase with movement up tributaries (the largest tide range in the Bay is found in the

Mattaponi River at Walkerton). The varying tide ranges makes the upper limit of tidal wetlands variable throughout the system.

The other complication is that the rate of sea level rise in the Bay is also variable. This is because local sea level change is a combination of both eustatic and isostatic changes. The first addresses global warming and the increase in total water volume in the ocean/estuary. The isostatic element addresses changes in the morphology/volume of the basin - i.e. local subsidence or tectonic processes. This later element is not consistent throughout the Bay region. Benchmark releveling undertaken by USGS researchers in the late 70's suggested that changes in isostatic sea level rise in the mid-Atlantic region varied from <1mm/yr to >2mm/yr (Personal Communication, Dr. Hershner). Added to eustatic sea level rise in the order of 2mm/yr, , the aggregate sea level rise rates can be significantly different from place to place incase of a tidal wetland (which in this region seems able to accrete vertically at a rate of <3mm/yr.)

The complications presented by varying upper limits of tidal wetlands and sea level rise necessitate a simplifying assumption about the general upper limit elevation. One could work to develop a more spatially explicit set of projections and impacts - but given the relatively limited range of variations in marsh elevations combined with the uncertainty in rates of sea level rise, any effort to improve spatial resolution may be futile. The mean tide range in the Bay varies from around 0.6 meters (2 feet) to just over 0.9 meters (3 feet). Using the average value of mean tide range of 0.75 meters (2.5 feet), it is concluded that the approximate rise in sea level that will completely inundate the tidal wetlands work out to be 1.125 meters (1.5 times 0.75 meters). The proportionate gain in wetlands for 'slr_t^{i}' increase in sea level in period t , Δ_t^{i} , is given by

$\Delta_t^{i} = \frac{'slr_t^{i}'}{1.125} * (W)$, where W denotes the total area of wetlands available.

2.5.3.4. Restoration Cost

Consistent estimates of restoration costs are difficult to obtain. Fonseca et al. (2001) report the distribution of the restoration costs among the various restoration tasks based on recent restorations plans that have been litigated in the Federal Court (Fonseca et al., 2001). For a 1.55-acre (6277 square meters) area, the total restoration cost is reported as \$590,000 in 1996 dollars. Adjusted for inflation, that amounts to \$734000 in 2005 dollars. The two major costs for sea grass restoration in general, and particularly for this analysis, are the planting costs and the monitoring costs. The planting costs constitute about 18.5 percent of the total costs. In 2005 dollars, the planting cost works out to be approximately \$22 per square meter of SAV planted.

Fonseca reports monitoring costs to be about 59 % of the total cost of restoration. That puts the magnitude of monitoring costs at approximately \$70 in 2005 US dollars per square meter of SAV restoration for a five-year period of restoration. The figure may look big but it reflects the fact that unlike planting that is a one-time event, monitoring entails labor intensive frequent undertakings over a long period of time. The information about costs is noisy and sensitivity analysis will be conducted to see to what extent the results of the analysis are dependent on the costs measures.

2.5.3.5. Discounting

There is much disagreement about the appropriate discount rate to use in economics to calculate present values that accounts properly for social time preference and risks. The debate is further intensified in environmental problems under uncertainty, As Pindyck (2007) points out that even if economists were to agree on the conceptual notion of correct discount rate (e.g. society's marginal rate of capital), there would still be considerable uncertainty over actual numbers to use for current and future discount rates (the marginal return on capital is difficult to measure, and its future evolution is marked with uncertainty). Discount rate uncertainty is amplified in problems with long time horizons. The OMB suggests the use of 3 % (and 7 %) for governmental regulatory analyses. The discount rate of 3 % is also widely used in literature in dynamic problems. A discount rate of 0.03 has been therefore been used throughout the analysis. The values for each time period is discounted back to the first period t_0, which is used as the base period. An infinite period discount factor is applied to the terminal period SAV benefit. All monetary values are expressed in 2005 dollars. Sensitivity analysis would also be conducted on the discount rate to evaluate the specifications influence on the results of the analysis.

2.5.3.6. Benefit Function-Choice and Calibration

SAV's as established earlier are valued for their habitat service and for improving water quality, services that are not entirely independent. The literature provides very little information on the economic value of the benefits of SAV restoration. Valuation studies have never been conducted specifically for SAV. Anderson (1989) used simulation methods to value the economic benefits of restoration for six select Virginia sites

(23000000 sq meters in area) for the hard shell blue crab fishery in Virginia. Anderson computed that restoring the SAV at the six sites would result in long run (his simulation run was for 15 years) annual benefits worth 1.8 million (1989 dollars) to the Virginian blue crab fishermen and 2.4 million (1989 dollars) to US consumers of blue crab. Together, the two surpluses total to 4.2 million (1989 dollars) or 7.23 million in 2005 dollars.

A logarithmic function is used for mapping the value of SAV benefits, $\mathrm{B(SAV)} = \mathrm{a}\log(\mathrm{SAV})$ with $B' > 0, B'' < 0$. The marginal benefit corresponding to this function is $\mathrm{MB(SAV)} = \frac{\mathrm{a}}{\mathrm{SAV}}$ and has unit elasticity. Experimentation with other functional forms with flexibility in elasticity did not make a difference to the analysis. The logarithmic specification is chosen to reflect the consensus among Chesapeake Bay policy makers that marginal benefit of additional SAV cannot be negative no matter how big the stock of SAV is.

2.5.4 Data

This section provides details on the acreage data of existing and historic SAV within the case study area. Virginia Institute of Marine Science (VIMS) obtained bathymetry information from the Chesapeake Bay Program. GIS information on the depth contours (bathymetry) is used to construct the depth zones for the restoration region within the case study area. Bathymetries are locus of points of equal water depth, much like the contour lines, which join points of equal elevation. The information was then used to create bathymetry bands (the depth zones) at incremental depth of 0.5 meters from the coastline all the way to the 3 meters water depth. The 1.5 meters line was interpolated from existing information using the program (Contour Gridder) run in Arcview Software. Coverage information of current (2001) SAV and historic SAV (1971-2001) was obtained from VIMS. The Wetlands Research Program at VIMS had completed the Tidal Marsh Inventory data in 1992. The above coverages were unioned together using GIS software ArcInfo. A frequency was run to determine areas of existing SAV, suitable SAV restoration regions within each bathymetry band, and the wetlands. The information was then compiled on an Excel spreadsheet that lists the area in square meters within each bathymetry band, the acreage of historic SAV, and current SAV within the bands and the acreage of the total wetlands available. The five-bathymetry bands thus constructed are used as the 5 depth zones in the model. Table 2-1 lists the acreage of (1) Historical and (2) Existing SAV in each zone or band. The area available of wetlands is 617000,000 square meters.

Table 2-1: Coverage area of existing SAV, historic abundance of SAV, and restoration region in each band, and of wetlands.

Bands/Depth Zones	Existing SAV	Historic SAV	Restoration Area (Historic – Existing)
1	29700	43700	14000
2	14800	28500	13700
3	2800	9500	6700
4	260	1100	840
5	110	880	770
Total	47670	83680	36010

Coverage Area reported in 1000 square meters

2.6 Results

2.6.1 Baseline

The Bay authorities' current restoration strategies were determined without any consideration of future sea level rise. As pointed out in the introduction, even without climate change, there will be some amount of sea level rise. The concern with climate change is that it will result in magnified sea level rise. To understand the impact of climate change induced sea level rise on optimal restoration strategies (as opposed to impacts arising from normal sea level rise), the optimization problem for determining optimal restoration strategies must be solved twice- once for the case 'without' climate change, and once for the case 'with' climate change. The optimization problem for the 'without' case accounts for climate change only to the extent that it contributed to the MSL at Seawells Point. 4.2 mm/year (MSL at Seawells Point) is used as the underlying sea level rise scenario for the model run without climate change. The sea level rise by the year 2030 is 12.9 cm in the 'without' case. The optimization routines are performed using the General Algebraic Modeling Systems (GAMS).

One of the challenges of this research has been the high level of uncertainty in the benefits and costs of restorations. Experimentation with these two components showed that the results (optimal area to restore in each depth band) are very sensitive to the benefit specifications (relative to the cost) for the model without climate change. Had restoration benefits and costs been known with certainty, it would have been possible to determine whether the current policy of restoring all areas of historical abundance (36, 010, 000 sq. m in the case study case) is optimal or not without climate change; the analysis could then examine whether the current policy is optimal or not when climate change is accounted for in the analysis. Current policy of restoring all historic area could well be sub optimal under climate change, but that cannot be examined unless one can establish that current policy is optimal without climate change. Not enough is known to establish the latter.

To understand whether restoration decisions change under climate change, the analysis assumes optimality of the current restorations strategy - i.e., the underlying premise is that without climate change, current policy is optimal. With respect to the benefits and the costs, the model is parameterized such the current policy of restoring all areas of historic abundance is the optimal outcome without climate change. In doing so, the uncertainty surrounding benefits is removed from the analysis, but a pro restoration bias is introduced in the model. However even with a pro restoration bias, if the results were to indicate that current policy is inefficient under climate change, then it would reflect the power of the result.

The next step in the analysis is therefore to calibrate the benefit function such that current strategy of restoring all areas of historical abundance is the optimal outcome of the model for the 'without climate change' scenario. Anderson (1989) simulation study had computed the value of the economic benefits of restoration for six select Virginia sites (23000000 sq meters in area) for the hard shell blue crab fishery in Virginia to be 4.2 million (1989 dollars) or 7.23 million in 2005 dollars(Anderson, 1989). However, calibrating the model with benefit value found in Anderson's study does not justify the current strategy of restoring all areas of historic abundance as the optimal outcome - it results in zero restoration in all zones in all time periods. Experimentation with calibration reveal that SAV benefits as established by Anderson's study have to be scaled up 600 times to justify complete restoration in the current period for Bands 1, 2, 3 under the 'without climate change' scenario (To justify complete restoration in all depth zones in the current period, the benefits have to be 1600 times of the SAV benefits of Anderson's study). Complete restoration in the current period for the three bands 1, 2, and 3 (without any restoration in Bands 4 and 5) constitutes 95% of targeted 2005 restoration region (i.e. targeted area under current policy) for the entire case study area. This calibration point yields the outcome that is a close approximation of the starting assumption for the analysis i.e. the current strategy of restoring all areas of historical abundance is the optimal outcome under the 'no climate change scenario'. Therefore, the calibrated model that results in complete restoration of the 3 bands as the optimal outcome under the model without climate change is chosen as the **baseline** for the 'without climate change' scenario. Parameter calibrations for the model without climate change that yields the baseline outcome will be called 'baseline' specifications.

The net present value of restoration for the model ''without climate change" under the baseline specification is $381 million (2005) dollars. Table 2-2 lists the restoration amount, emergent SAV, and total SAV stock (in 1000 square meters) for each period under the baseline scenario. For the three bands, all available area is restored in the first period. Across time, the optimal amount of restoration for each band decreases and there is less restoration in the shallow bands relative to the deep bands - i.e. there is less restoration in band 1 (band2) in time periods 3, 4, and 5 compared to restoration in bands 2 and 3 (band 3). The increase in the sea level impacts tolerable water depth most for sites that are already in deep water, resulting in greater loss of SAV in the deep bands.

The greater loss of SAV in the deep bands in turn requires greater restoration in the deep bands. There is a great increase in the total SAV stock in the initial period following restoration of all three bands, with minor incremental jumps after that. By 2030, the total stock of SAV achieved, through restoration and submerged tidal wetlands, exceeds the historically known SAV abundance. The total stock of SAV at 2030 is 72% higher than 2005 existing stocks.

Table2-2: Restoration strategies, emergent SAV, and total SAV under the baseline/ ‘Without Climate Change’ scenario[2]

Extent of Restoration Level					
Depth Bands	Time Periods				
	2005-2010	2011-2015	2016-2020	2021-2025	2026-2030
1	14000	5363	2504	1490	1119
2	13700	7052	3903	2381	1635
3	6700	4843	3571	2698	2095
4	0	0	0	0	0
5	0	0	0	0	0
Emergent SAV	0	2852	4278	5704	7130
SAV	65590	75814	80697	83869	86224

2.6.2 Climate Change

2.6.2.1 Scenarios for Sea Level Rise

There are two components of sea level rise- (1) eustatic sea-level rise (SLR) or a global component that reflects thermal expansion of the ocean, decreases in surface water and groundwater storage, and glacial melting, and (2) a local component that reflects vertical land movements resulting from regional tectonics , post glacial isostatic

[2] Figures in thousand square meters

adjustments, compaction, and surface subsidence. Relative Sea Level Rise (RSLR) refers to the sum of the two components.

The National Oceanic and Atmospheric Administration (NOAA)'s National Ocean Service (NOS) Center for Operational Oceanographic Products and Services (CO-OPS) collects and distribute observations and predictions of water levels and currents (NOAA Sea Levels Online, 2007). (CO-OPS) data from 1935 to 1999 for Sewells Point, Hampton Roads establish a mean sea level (MSL) trend of 4.12 millimeters (0.016 inches) per year.

Probability based projections of estimated future sea level rise has been developed by (Titus and Narayanan, 1995). Their estimates of sea level rise exclude the contribution of non-climatic factors and include only the contribution of climate change to sea level rise. They develop normalized projections that estimate the extent to which future sea level rise will exceed what would have happened if current trends simply continued. Projections of sea level rise for a specific location (j) can then be obtained by simply adding the normalized projection to the current rate of sea level rise at location j:

$$local_j(t) = normalized(t) + (t - 1990) * trend_j \tag{2.10}$$

Assuming that the non-greenhouse factors stay constant these normalized projection represent the extent to which sea level rise will exceed the rise that would be expected from extrapolating the historic rate of rise. Plugging the value of MSL trend of 4.12 millimeters per year in Equation (2.10) reveals that the median sea level rise will be 20.47 cm (8.06 inches) by 2025 for Sewells Point. The lower and upper bounds for the projections are 5.47 mm (2.15 inches) and 34.47 mm (13.5 inches) respectively. It is to be noted that these projections only include the contribution of the non-climatic factors only as to the extent that their contribution is captured in the historic sea level rise trends at these locations. Any aggravation in the contribution of the non-climatic factors to sea level rise will alter these projections.

Data on relative sea level rise from long term tide gauges in the Chesapeake Bay region reveals that Chesapeake region has a systematically higher rate of sea level rise than the long term global average. Much of the difference is believed to have been on account of localized subsidence caused by ground water extraction, an activity that is known to be on the rise in the Chesapeake Bay Region (NGS, 1997). Consequently there exists the possibility that the best estimates from the Titus and Narayanan approach will still underestimate the true sea level rise for this region.

The Mid Atlantic Regional Assessment (MARA), one of the 19 regional assessments conducted under the auspices of the U.S. Global Change Research Program, reported the projections for sea level rise for the Mid Atlantic Region in (MARA, 2000). Hampton Roads is a subset of the MARA Region. MARA projects that sea level will be 19 cm (7.5 inches) and 66 cm (26 inches) higher than the 1990 level by year 2030 and 2095 with high reliability of predictions.

Combining input from the Titus and Narayanan and the MARA study, the projections for plausible sea level rise (by the year 2030) for Hampton Roads, Virginia for this study is bounded between 11 and 35 cm (4 to 13.7 inches). The mean sea level rise is fixed at 21 cm (8.26 inches). The study considers three scenarios of sea level rise denoted as low (l), medium (m), and high (h) respectively. Table 2-3 lists the three sea level rise scenarios considered in this study. The magnitude of annual sea level rise and the total sea level rise expected by the year 2030 under each of the scenarios is also reported in Table 2-3. Sea level is assumed to rise linearly.

Table 2-3: Three scenarios of sea level rise

Scenarios (ω)	Mean Sea Level/Year		Sea Level Rise by 2030	
	Millimeters	inches	(meters)	(inches)
Low (l)	5	0.20	0.15	5.91
Medium (m)	7	0.28	0.21	8.27
High (h)	10	0.39	0.30	11.81

Table 2-4 illustrates the method by which probabilities for the three scenarios of sea level rise considered in this study were determined. To ascertain the probabilities, the cumulative probability as established by Titus and Narayanan for the range of sea level rise in their study (5.47-34.7 cm) is taken and applied over the range of sea level rise considered in this study (11-35cm). In order to do so, the probability in the Titus and Narayanan study for $5.47<x<14.47$cm is distributed between $11<x<15$ cm in this study.

Table 2-4: The probability of sea level rise in this study[3]

Cumulative Probability	Probability Density	Sea Level Rise		
		(T&N)	This Study	
1	1	5.47	11	
5	4	12.47	13	
10	5	14.47	15	Low (Probability = 0.3)
20	10	16.47	17	
30	10	18.47	19	
40	10	19.47	20	
50	10	20.47	21	Medium (Probability = 0.5)
60	10	21.47	22	
70	10	23.47	24	
80	10	24.47	25	
90	10	27.47	28	
95	5	29.47	30	High (Probability = 0.2)
97.5	2.5	32.47	33	
99	1.5	34.47	35	

Table 2-4 reports the cumulative probability and probability densities for the sea level rise for Seawell's Point as obtained from the Titus and Narayanan study for the sea level rise range used in this study. The entire range 11-35 cm is divided into three groups (11-19, 19-25, 25-35 cm) and the corresponding probability distribution is accordingly condensed for these three intervals. The mean values of the three intervals are the three

[3] The mean sea level rise of 22 cm in the medium range is different from the scenario of 21 cm

(low, medium, and high) sea level scenarios in this study. The probabilities corresponding to the low, medium, and high scenarios of sea level rise are 0.3, 0.5, and 0.2. Sensitivity analysis will be conducted on the specifications of the probabilities too.

2.6.2.2 Results under Climate Change

The model with climate change is run with the baseline specifications for the parameters. The probabilities $p^i = 0.3, 0.5, 0.2$ corresponding to low, medium, high scenarios of sea level rise deduced from the Titus and Narayanan study is used as the probabilities for the three scenarios of sea level rise in the run of the model with climate change. The results for climate change are reported in Table 2-5; the numbers in the table represent percentage change from optimal restoration outcomes under the baseline 'without climate change' scenario.

Under the baseline specifications, restoration strategies do not diverge between the 'without' and 'with' climate change runs of the model for the first period. Differences arise in the restoration choices of the later periods. For the low sea level rise scenario, optimality requires slightly greater restoration for all 3 bands, with the need of restoration being the greatest (15 % more than the without climate change scenario) in band 1 in the last time period 4 (Year 2026-2030 in the 2030 planning horizon). Optimality requires even greater restoration for the 3 bands under the medium sea level rise scenario, with the magnitude of the greater restoration required increasing as once goes across time. For medium sea level rise scenario, optimal restoration requires 63%, 36%, and 13% greater amount of restoration relative to the case without climate change for band 1, 2, and 3 respectively in the last time period. This results are intuitive - with sea level rise, the greatest chance of survival of the restored SAV is in the shallow bands where the impacts of sea level rise is relatively less than the other bands. Greater restoration efforts are therefore dictated in band 1 under optimality.

An interesting result emerges with Band 3 under the high sea level rise scenario. For the high sea level rise scenarios, optimality under climate change calls for zero restoration in Band 3. This is different from the results for Band 3 under the low and medium sea level rise scenario, under which optimality had dictated greater restoration than the optimal amounts determined under the case without climate change. Two drivers nullify the need to restore SAV in Band 3 under the high sea level rise scenario; (1) the big gain in the emergent SAV obtained from the tidal wetlands (130% more than the emergent SAV gain under the baseline), and (2) the relatively greater propensity for SAV loss in the deep bands. It must be noted that wetlands provide a larger opportunity for SAV restoration under climate change.

The total stock of SAV at the end of year 2030 under climate change is more than the stock achieved under the baseline for all three-climate scenarios. A fascinating revelation from the results is that the sea level rise actually is good as it leads to the creation of more SAV than would occur without sea level rise. This is only possible if the wetlands remain available and therefore reflects the importance of the assumption of emergent SAV in the model. The Expected Net Present Value (ENPV) under climate change is $ 381.87 million (2005 dollars), a gain of 2% over baseline value.

Table 2-5: Restoration strategies, emergent SAV, and total SAV under climate change

Percentage change in restoration across time relative to baseline					
Bands	Time Period				
	2006-2010	2011-2015	2016-2020	2021-2025	2026-2030
	LOW				
1	0.00	1.27	5.67	10.87	15.10
2	0.00	0.38	2.38	5.29	8.75
3	0.00	0.10	0.78	1.74	3.05
4	-	-	-	-	-
5	-	-	-	-	-
Emergent SAV	0.00	15.39	15.38	15.38	15.37
Total SAV	-0.15	0.41	0.58	0.78	0.98
	MEDIUM				
1	0.00	4.96	22.72	44.50	63.18
2	0.00	1.53	9.48	21.34	35.84
3	0.00	0.41	3.16	7.12	12.51
4	-	-	-	-	-
5	-	-	-	-	-
Emergent SAV	0.00	61.54	61.52	61.52	61.53
Total SAV	-0.60	1.66	2.30	3.07	3.85
	HIGH				
1	0.00	10.24	48.00	97.05	141.82
2	0.00	3.19	20.11	46.07	78.84
3	0.00	-100.00	-100.00	-100.00	-100.00
4	-	-	-	-	-
5	-	-	-	-	-
Emergent SAV	0.00	130.75	130.76	130.77	130.76
Total SAV	-1.24	1.80	2.02	2.85	3.93

In summary, the results indicate that for low and medium sea level rise, the optimal response under climate change requires substantial more restoration in all bands relative to the case where there is no climate change-the farther out one goes into the future, the greater is the difference between the two scenarios. But if the high scenario were to materialize then the optimal response would be to concentrate restoration effort in the shallow bands 1 and 2 and pursue no restoration in the relatively deep band 3. The outcome is logical as the loss of restored SAV is relatively less for the shallow bands compared to deep bands and will have more SAV to contribute to the terminal stock in 2030.

2.6.3 Sensitivity analysis

The baseline run of the models used a specific set of estimates for the parameters. Sensitivity analysis is conducted to check how robust the results are to the specifications and assumptions of the baseline models. Specifications for both the model without climate change and the model with climate change are altered, and then optimal restoration strategies under climate change (defined as percentage change from optimal restoration area established under the model without climate change) are determined under the altered specification. Optimal strategies under climate change resulting from this approach are then compared with optimal strategies under climate change as established by the baseline run to examine the effect of the parameters on the analysis.

2.6.3.1 Probabilities

Climate scenarios, as stated earlier, are defined by the sea level rise and the probability associated with sea level rise. Experimentation with probability specifications different from the baseline show that the results obtained under the baseline run remains invariant with most other specifications. It is only when the probability distribution over the three scenarios becomes extremely skewed towards the high scenario that the results under climate change vary from the baseline results. Table 2-6 contrasts the outcome under climate change under the baseline run with the outcome under climate change corresponding to probability specification of {p(low), p(medium), p(high)}={0.05,0.15,0.8}. The optimal amount for Band 3 in the initial period 2006-

2010 under climate change is 19 % less than of the optimal restoration for Band 3 under the ‘no climate change’ case. This is different from the baseline results where the outcomes for with and without climate change were identical. Also for each period between 2011 and 2030, the optimal state contingent choices for Band 3 are higher under the alternative probability specification compared to the baseline outcome for the low and medium level of sea level rise. The latter is a result of having more area available for restoration in the successive periods that follows from the low initial period restoration for this band and also from having relatively less wetlands gain under these two scenarios of sea level rises.

Table 2 – 6: Restoration strategies under climate change under different probability specifications[4]

Probability Specifications											
Baseline						{p(low), p(medium), p(high)}={0.05,0.15,0.8}					
Bands	Time Period					Bands	Time Period				
	2006-2010	2011-2015	2016-2020	2021-2025	2026-2030		2006-2010	2011-2015	2016-2020	2021-2025	2026-2030
	LOW						LOW				
1	0	1.27	5.67	10.87	15.1	1	0	1.27	5.67	10.87	15.10
2	0	0.38	2.38	5.29	8.75	2	0	0.38	2.38	5.29	8.75
3	0	0.1	0.78	1.74	3.05	3	-19.07	7.58	7.92	8.41	9.16
4	-	-	-	-	-	4	-	-	-	-	-
5	-	-	-	-	-	5	-	-	-	-	-
	MEDIUM						MEDIUM				
1	0	4.96	22.72	44.5	63.18	1	0	4.96	22.72	44.50	63.18
2	0	1.53	9.48	21.34	35.84	2	0	1.53	9.48	21.34	35.84
3	0	0.41	3.16	7.12	12.51	3	-19.07	7.85	10.19	13.71	18.52
4	-	-	-	-	-	4	-	-	-	-	-
5	-	-	-	-	-	5	-	-	-	-	-
	HIGH						HIGH				
1	0	10.24	48	97.05	141.82	1	0	10.24	48.00	97.05	141.82
2	0	3.19	20.11	46.07	78.84	2	0	3.19	20.11	46.07	78.84
3	0	-100	-100	-100	-100	3	-19.07	-100	-100	-100	-100
4	-	-	-	-	-	4	-	-	-	-	-
5	-	-	-	-	-	5	-	-	-	-	-

[4] Numbers in table are the outcomes under climate change presented as percentage changes from the outcomes under no climate change

2.6.3.2 Time Horizon

The length of the planning periods on the SAV restoration strategies is next examined. Table 2-7 lists the restoration strategies under climate change (as percentage changes from the restoration under the no climate change case) for time horizons of 2025 and 2035 respectively. It is again for Band 3 that the results differ from the baseline, but only for medium and high sea level rise. For medium sea level rise, for horizon 2035, restoration in Band 3 calls for zero restoration from 2016 onwards. In the extra period 2030-2035 over the baseline, optimality dictates greater restoration of the shallower bands (1 and 2) than Band 3 as the SAV restored in those bands will be better retained when the sea rises further. Longer horizons favor repeated restoration of most productive bands.

Table 2 – 7: Restoration strategies under climate change under different time horizons

Sea Level Rise Scenario	Time Horizon	BANDS	2005-2010	2011-2015	2016-2020	2021-2025	2025-2030	2030-2035
LOW	2025	1	0	1.28	5.69	10.89	-	-
		2	0	0.38	2.36	5.28	-	-
		3	0	0.11	0.77	1.76	-	-
	2035	1	0	1.27	5.70	10.90	15.14	17.76
		2	0	0.39	2.36	5.28	8.76	12.15
		3	0	0.11	0.78	1.77	3.09	4.71
MEDIUM	2025	1	0	4.97	22.74	44.52	-	-
		2	0	1.53	9.46	21.32	-	-
		3	0	0.42	3.15	7.13	-	-
	2035	1	0	4.98	22.73	44.52	63.20	75.51
		2	0	1.52	9.45	21.33	35.88	50.45
		3	0	0.43	-100	-100	-100	-100
HIGH	2025	1	0	10.24	48.03	97.08	-	-
		2	0	3.19	20.09	46.05	-	-
		3	0	-15.48	-100.00	-100.00	-	-
	2035	1	0	10.24	48.02	97.09	141.87	173.58
		2	0	3.18	20.08	46.04	78.87	113.01
		3	0	-100	-100	-100	-100	-100

For the high sea level rise scenario, under the baseline specification, the optimal strategy was to restore all of Band 3 in the initial period, and then not to restore after that. When the time horizon is restricted to 2025, the optimal strategy is to lower restoration in Band 3 by 15.48 % in the period 2011-2015 –this is in contrast to the optimal outcome of zero restoration for this period under the baseline specification. The economics behind the result has to do with how the present value of the benefits. Using the same discount rate, the present net value of a unit of SAV restored in Band 3 will have a greater value under a shorter time horizon than a longer time horizon. Additionally, a shorter horizon results in less cumulative sea level rise in the model, in turn resulting in greater proportion of a unit of restored SAV surviving as the terminal stock. The discounted value of the benefits that will accrue from the addition made to the terminal stock of SAV made to the terminal stock under the longer horizon of 2035. The difference in benefits justifies restoration of Band 3 by a unit of SAV restored in band 3 is greater than the present value of the of the addition

2.6.3.3 Costs

In the baseline analysis, the costs of restoration had been fixed at $22 for planting costs and $70 for monitoring costs for each square meter of restoration. The effect of restoration costs on the restoration choices under climate change is now examined. Table 2 - 8 lists the outcome under climate change for high and low costs-the figures show the percentage increase in restoration under climate change from the 'without' climate change case. The high cost represents the case where the monitoring and planting costs are double of the baseline specification i.e. they are $140 and $44 respectively. The low costs represent the case where the monitoring and planting costs are set at half of the baseline costs i.e. $35 and $11 respectively.

In the baseline run without climate change, optimality calls for the restoration of the three bands 1, 2, and 3. With lower costs, even without climate change, it is optimal to restore Band 4 as well. In contrasts when the costs are high, the optimal outcome under 'no climate change' case is to restore Bands 1 and 2 only. The optimal strategy under climate change calls for less restoration (for medium or high level of sea level rise) under the high cost scenario and more restoration under the low cost scenario - under the latter optimality requires restoring Band 3 in all years between 2011-2030 and also Band 4 in all years. Results are very sensitive to costs specifications and therefore costs play a very important role in determining restoration strategy under climate change.

Table 2 – 8: Restoration strategies for high cost and low cost

Percentage change in restoration across time relative to case without climate change											
HIGH COSTS						LOW COSTS					
Bands	Time Period					Bands	Time Period				
	2006-2010	2011-2015	2016-2020	2021-2025	2026-2030		2006-2010	2011-2015	2016-2020	2021-2025	2026-2030
	LOW										
1	0.00	1.28	5.69	10.89	15.10	1	0	1.28	5.69	10.89	15.10
2	0.00	0.38	2.38	5.29	8.75	2	0	0.38	2.38	5.29	8.75
3	-	-	-	-	-	3	0	0.10	0.78	1.74	3.05
4	-	-	-	-	-	4	0	0.15	0.77	1.66	2.86
5	-	-	-	-	-	5	-	-	-	-	-
	MEDIUM										
1	0.00	4.97	22.74	44.52	63.18	1	0	4.97	22.74	44.52	63.18
2	0.00	1.53	-100.00	-100.00	-100.00	2	0	1.53	9.48	21.34	35.84
3	-	-	-	-	-	3	0	0.41	3.16	7.12	12.51
4	-	-	-	-	-	4	0	0.30	2.88	6.64	11.43
5	-	-	-	-	-	5	-	-	-	-	-
	HIGH										
1	0	10.24	48.03	97.08	-100	1	0	10.24	48.03	97.08	141.73
2	0	-100	-100	-100	-100	2	0	3.19	20.11	46.07	78.84
3	-	-	-	-	-	3	0	0.89	6.72	15.34	27.11
4	-	-	-	-	-	4	0	0.61	6.14	14.22	24.86
5	-	-	-	-	-	5	-	-	-	-	-

2.6.3.4 Discount Rates

The effect of discount rate on the restoration choices is very similar to the effect of the costs on the restoration choices. The baseline rate was 3 %. Table 2.9 lists the optimal responses to climate change under high and low specifications of discount rate. For a rate higher than that (say 5%), the optimal outcome under no climate change results in restoration of the two shallow bands, Band 1 and 2. The extent of restoration at these two bands is same as the extent as obtained in the baseline run. Under climate change with the 5 % discount rate, the optimal response is the same as the response under the baseline run for Bands 1 and 2 under all the three scenarios of sea level rise with the only difference being zero restoration in Band 2 in the final period (2026-2030). Higher discount rate favors the more productive bands first and also restoration in the nearer periods over farther periods. The results are different for a low interest rate (1 %). All five bands are restorable under no climate change for a low discount rate. Under climate change and a discount rate of 0.01, the optimal response is different from the results under the baseline case for the bands 1, 2, and 3 in that greater restoration (than the without climate change case) is not preferred in the initial periods. Even with bands 4 and 5, which were not restored under the baseline run, optimality under climate change indicates that restoration, if any, is preferred in the later periods where they can contribute more towards the terminal stock, which has a high value as the discount rate is so low.

Table 2 – 9: Restoration strategies under different discount rate

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Percentage change in restoration across time relative to case without climate change											
HIGH DISCOUNT RATE (0.05)						LOW DISCOUNT RATE (0.01)					
Bands	Time Period					Bands	Time Period				
	2006-2010	2011-2015	2016-2020	2021-2025	2026-2030		2006-2010	2011-2015	2016-2020	2021-2025	2026-2030
	LOW										
1	0.00	1.28	5.69	10.89	15.13	1	0	1.28	5.69	10.89	15.13
2	0.00	0.38	2.36	5.28	8.76	2	0	0	2.36	5.28	8.76
3	-	-	-	-	-	3	0	0	0.78	1.77	3.09
4	-	-	-	-	-	4	0	0	0.68	1.57	2.74
5	-	-	-	-	-	5	-100	13	12.40	11.83	11.43
	MEDIUM										
1	0.00	4.97	22.74	44.52	63.22	1	0	4.97	22.74	44.52	63.22
2	0.00	1.53	9.46	21.32	35.86	2	0	1.53	9.46	21.32	35.86
3	-	-	-	-	-	3	0	0	3.14	7.15	12.53
4	-	-	-	-	-	4	0	0	2.77	6.41	11.24
5	-	-	-	-	-	5	-100	-100	-100	41.31	39.20
	HIGH										
1	0.00	10.24	48.02	97.09	141.87	1	0	10.24	48.02	97.09	141.87
2	0.00	3.18	20.08	46.04	-100.00	2	0	3.18	20.08	46.04	78.87
3	-	-	-	-	-	3	0	0.90	6.71	15.38	27.16
4	-	-	-	-	-	4	0	0.55	6.02	14.03	24.85
5	-	-	-	-	-	5	-100	-100	-100	-100	-100

2.7 Value of Wetlands Protection in Context of SAV Restoration

The implicit assumption in the analysis so forth has been that the wetlands would be available and also ecologically compatible for becoming a SAV growing area. The tidal marshlands are protected under current Wetlands Protection Program in Virginia. The wetlands protection ensures availability of the tidal marshes as a future SAV site. Here, we examine the importance of having the wetlands available for SAV migration for SAV restoration by analyzing the case where they are not available.

The wetlands gain contributes to the stock of emergent SAV thereby reducing the amount of SAV that needs to be restored. In the baseline scenario, decreasing the amount of wetlands gain to zero decreases the NPV of SAV restoration from 381.04 million dollars to 377.75 million dollars. The welfare under climate change reduces from 381.87 to 376.72 million dollars in the absence of the wetlands. Obviously the welfare loss (5.15 million dollars) from the unavailability of the wetlands is magnified under climate change, as more SAV lost to sea level rise and there is none available from submerged wetlands. The wetlands protection program in Virginia ensures welfare worth 21 million dollars in the case of no climate change for SAV restoration and of 43 million dollars in case of climate change.

The wetland protection acts as an insurance against future losses of SAV and is a good adaptation measure in context of climate change risks to natural resources and ecosystems.

2.8 Conclusions

The main question posed in this analysis is whether SAV restoration strategies as pursued now will differ or not in the case of future climate change. In a model focused on considering the impact of climate change induced sea level rise on SAV restoration, the simulation results clearly indicate that restoration choices under the baseline model are different from the choices under the climate change model. This has important policy implications for the SAV restoration program in the Chesapeake Bay. A restoration target that requires restored SAV at all site known to have historical abundance, as is currently being pursued in the Bay, is not the optimal restoration strategy when one considers climate change-optimal decision making under climate change requires less restoration at historic sites in deep water as the restored SAV in these sites will be eliminated by the rising sea level. Optimality dictates that restoration effort be undertaken at shallow sites where the loss of restored SAV is minimal. In the absence of the reliable information on the true values and costs, it is not possible to establish whether the current policy of restoring all is optimal even without climate change. The study adopts the premise that the current policy of restoring all is the optimal restoration decision under the baseline, i.e. the case without climate change. In doing so it incorporates a pro restoration bias. The study chooses that value for SAV benefits that allows the current policy of restoring all areas of historical abundance in the productive depth zones (Bands 1, 2, and 3) to be the optimal outcome under the baseline. Within the same range of value specification, results show that the same restoration policy is not the optimal outcome when one takes climate change into account - optimality requires less restoration for the deep bands and more restoration for the shallow bands under climate change. This is an important finding as it shows that even with a restoration bias built into the model; optimality requires less restoration under climate change for the sites located in the deeper water.

Climate change calls for site specific restoration area adjustments (more restoration in the shallow bands and less restoration in the deep bands), and the magnitude of the site specific adjustments required under climate change depends upon the interplay of factors like benefits and costs of restoration, availability of wetlands, characterization of the uncertainty over climate change. In cases where the benefits are high relative to restoration costs, it is optimal to restore more than (current policy) targeted area of historic abundance of SAV. Climate change does not matter in this case as the benefits to be gained from restoration over the time horizon will outweigh the costs of repeatedly restoring the SAV lost to sea level rise. On the other hand, in cases where the costs are high relative to benefits (or the discount rate is high), optimality calls for less restoration under climate change than the historic amount, specially for the future time periods-the present value of the low benefit that are discounted heavily does not justify the high costs of restoring the SAV that is lost to rising sea level. Wetlands represent an opportunity for SAV under changed climate and are of great importance to the restoration process.

An adaptive restoration strategy would be to undertake more restoration in the shallow regions of the Bay relative to the deeper region of the Bay. As SAV thrives better is shallow water, the risk of unsuccessful restoration and elimination of the restored SAV to a rise in sea level is more at sites in the deep water zones. Given the uncertainty regarding sea level rise, the ‘wait and watch’ attitude would be beneficial before undertaking restoration at sites located in bands 3, 4, and 5 i.e., restoration should only be implemented at sites in the bay where the water depth ranges from 0.5 meters to 1.5 meters. As time passes and policy makers become more aware of the state of sea level rise, they can adjust their restoration choices. If sea level rise is slow or less than what is expected, restoration area choices can be expanded to include sites in deep water. If on the other hand, sea level rise is accelerated and more than what is expected currently, restoration area choices can be same as before (no restoration in bands 3, 4, 5) or modified to concentrate on even smaller areas within bands 1 and 2.

The greatest improvement in decision-making involving SAV restoration in the Chesapeake Bay would come form knowing the benefits and costs of SAV restoration. This study finds that with respect to uncertainty, there appears to be more reliable information on climate variables (sea level rise in our case) than information on the economic values of natural resources and ecosystems that are targeted for adaptation. Valuing the benefits of SAV poses the challenge of valuing the indirect marketable value of SAV as captured in the market values of the crabs and the direct non-marketable water quality improvement service that SAV provides. The value of information for SAV benefits is very important, as it will enable the decision makers in the Chesapeake Bay Program to make better decisions with respect to their restoration choices.

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ESSAY 3

INTEGRATED SAMPLING OF THE ECONOMY AND THE ENVIRONMENT

3.1. Introduction

A comprehensive watershed based approach to water quality management that focuses on in-stream conditions, management of both point and nonpoint sources of water quality degradation, and promotes cost-effective pollution reductions, is now widely accepted as the appropriate way to address water quality problems (USDA and USEPA, 1998; NRC, 1999; USEPA, 2001). Although there is much to be said in the favor of such an approach, a significant barrier to realizing the gains is the extensive information needed about pollution sources, water quality conditions, relationship between land uses and pollution loads, and pollution loads and water quality. As highlighted by a recent National Research Council Report (NRC and Council, 2000), such essential information is often lacking. The NRC report emphasizes the essential role of strategic information acquisition by water quality managers for improving the effectiveness and efficiency of water quality management.

Because information acquisition is costly, decisions are required on how much of different kinds of information to invest in, and on the strategies (like sampling) used for obtaining information. The Expected Value of Information (EVOI), defined as the increase in the expected value of the decision maker's objective function resulting from the acquisition and use of additional information, is often used as a measure of the contribution of additional information in decision making under uncertainty (Lawrence, 1999). Essentially, what EVOI does is to expand decision analysis to evaluate the benefits of collecting additional information that reduces or eliminates uncertainty in a specific decision making context. The analysis makes explicit the expected potential losses from errors due to uncertainty and identifies as "best" the information collection strategy that delivers the greatest net benefit to the decision maker (DM) (Yokota and Thompson, 2004). EVOI is defined as an expected value because the findings of the information collection, and in consequence, the decisions that would be made based on the new findings, are uncertain prior to the information acquisition.

In efficient water quality management, sources of uncertainty are scientific (lack of information on water body response to pollution; imperfect knowledge about pollution fate and transport) and economic (pollution control costs). While the former arises because of our imperfect understanding and inability to measure complex interrelated environmental services, the latter emerges because policy makers operate in an environment of asymmetric information where the economic costs of pollution control needed for policy design are known to the polluters but not to the water quality manager. For cost-minimization and optimal risk management, planners must choose both the control instrument and the level of the instrument based on knowledge of abatement costs across the watershed landscape (Shortle and Horan, 2002). Such information is not available to the planners.

The tradeoff in watershed based pollution management is between information cost, the and efficiency of policy design- the more site specific information the regulator has, the more efficiently he or she can design pollution control policies that minimize abatement costs and manage water quality risks. Information has value in terms of increased ability to reduce pollution control costs and achieve water quality objectives with greater certainty.

Environmental data collection is typically focused on sampling physical, geological, climatic, and other environmental characteristics within watersheds. This is nowhere more true than in the case of TMDL - since the passage of the Clean Water Act (CWA) 27 years ago, significant data collection and research efforts undertaken to improve the scientific base upon which TMDLs can be established have concentrated more on developing the physical science knowledge base, largely sidestepping the social and economic component on which policy design and water quality standards hinges (Mausbach and Dedrick, 2004). Recognizing the importance of costs in water quality policy design, the 2000 Clean Watersheds Needs Survey asked for states to report their costs of non point pollution control; lacking the resources to develop such estimates most states failed to report or provided minimal information (USEPS 2003). More recently, Secchi (2005) combined economic and watershed based hydrological models with data on land use and conservation practices to estimate abatement costs for specific water quality changes; such efforts are emergent and rare. Little effort has been expended in exploring the worth of farm level economic data that can reduce planners' uncertainty about the costs of agricultural pollution control.

This essay explores the value of additional information in improving the cost efficiency of nonpoint pollution control policy design. The analysis focuses on the management of agricultural water pollution using nitrogen pollution from corn production using Conestoga watershed in Pennsylvania as a case study. Specifically, the study examines the EVOI of alternative sampling strategies of the watershed's environment and the economy in nitrogen pollution management under standards as the control instrument. The emphasis is on investigating the EVOI of 'integrated' sampling strategy, where 'integrated' implies joint collection of environmental and economic information at the point of sampling. The investigation will help inform the hypothesis that integrated sampling of the environment and the economy is a superior approach for obtaining information than exclusive environmental sampling of the economy, within the context of pollution control minimization decision problem and case study setting. A high value of EVOI argues in favor of investing greater research effort and potential resources in reducing economic uncertainty in watershed based approaches to managing water quality.

3.2. Objectives and Methodology

The primary objective of this essay is to examine the EVOI of integrated sampling for environmental and economic information for water quality management. The essay first estimates, in the context of a stylized agricultural nonpoint pollution problem, the EVOI of environmental sampling of pollution loads. Environmental sampling here refers to sampling the watershed for characteristics like distance to river, distance to mouth of watershed, soil types etc that leads to an estimate of the contribution of different parts of the watershed to the total loading i.e. determining the pollution impact types of the different parts of the watershed. The essay then estimates, in context of the same problem, the EVOI of integrated sampling of the economy and the environment. Economic information within an integrated sampling strategy would include information relevant to the economic costs of pollution abatement. In the context on nitrogen abatement in agriculture, such information would corn yield responses to changes nitrogen applications rates, and soil nitrogen at the locations being sampled for environmental information, thereby enabling estimation of agricultural (economic) productivity type of the different parts of the watershed.

The two EVOI measures of exclusive environmental sampling and integrated sampling of the environment and economy enable comparison of the relative performance of the two information structures in serving water quality management decision-making problems within the watershed. A secondary objective is to explore the robustness of measured EVOI to alternative integrated sampling strategies that are differentiated by location choice of the sampling points and sample size.

Since measures of EVOI are tied to the specifics of the DM's problem, embedded within the objective of estimating EVOI is the need to clearly define the context of the DM's problem i.e. set the specifics for the water shed based water quality management problem. At the heart of the analysis is a coupled model of agricultural production and pollution loads in a watershed to simulate the economic costs of changes in agricultural to reduce nutrient runoff in sub areas of the watershed. To frame the decision problem, the essay uses a stylized case of nutrient management in the Conestoga River Watershed (CRW) in Lancaster County, Pennsylvania. The CRW is a sub watershed of the Susquehanna River Basin (SRB) and is a part of the larger Chesapeake Bay watershed. The CRW has the highest nutrient concentration of any watershed flowing into the Susquehanna River and the river is drastically impaired from nitrogen and phosphorus pollution (Little Conestoga Watershed Alliance, 2006). The main sources of this pollution include runoff from animal waste and excessive commercial fertilizer. Other pollution sources are sediments from intense cropping, development, and urban runoff. The SRB contributes over 40 percent of the Chesapeake Bay's excess nitrogen and phosphorus and much of it derived from the five million tons of livestock manure produced annually in Lancaster County (Little Conestoga Watershed Alliance, 2006).

The analysis abstracts from reality by assuming that the only crop produced is corn, the only nutrient of concern is nitrogen, and that nitrogen pollution in the CRW arises exclusively from corn production in the watershed. The goal of nutrient reduction, specifically nitrogen reduction, within the CRW is the targeted environmental goal in the EVOI analysis.

The policy instrument considered in the analysis for nitrogen loading reduction is standards (quantity control) applied to nitrogen fertilizer. The corn yield for each field is modeled as a function of the soil (productivity) type of the field and nitrogen fertilizer application. The baseline is defined as the case without any regulation. Assuming farmers are technically and allocatively efficient, profits are restricted once standards are imposed on fertilizer application. The difference between baseline profits and restricted profits are modeled as the abatement costs of pollution control. Variation in the soil type drives the differences in corn yield across the fields, thereby generating heterogeneity in the economic costs of pollution control across the watershed.

The nitrogen loading from each field is also modeled as a function of the soil type and the nitrogen application rate. Nitrogen dissipation during transport through the streams is modeled as a function of the distance traveled through the streams. Soil type at a given location and its distance from the mouth of the watershed determines the pollution type of the location, and variations in these two variables drive the heterogeneity in net pollution loads from different parts of the watershed.

For the analysis, the agricultural land within the CRW is divided into irregular polygons termed crop production areas that are defined on the basis of the soil type. Soil type of a location is a major determinant of both agricultural productivity as well as the contribution to total pollution from that location. Division of watershed areas in terms of soil characteristics and distance enables classification of the crop production areas in terms of agricultural productivity types and pollution impact types. Existing GIS information on soil types within the CRW was used to create the crop production areas and determine the proximity of the area to the mouth of the watershed. AVGWLF, a GIS based water assessment tool developed by the Pennsylvania State University's Institute of the Environment, which facilitates the use Generalized Watershed Loading Function (GWLF) watershed simulation model, in an Arcview (GIS software) interface is used to simulate individual pollution loads for each crop production areas created.

Sampling for the economic information occurs at the field level because the field is the unit at which fertilizer application decisions are taken. In the absence of readily usable information on the actual location of the fields in the CRW, the cornfields on the watershed landscape were simulated using ArcGIS software. The EVOI analysis thus depends on Monte Carlo simulation rather than sampling of actual fields. First, soil nitrate levels (determined by fertilizer applications and soil type), corresponding corn yield, and attenuated nitrogen loads are simulated for each (simulated) cornfield in the watershed through the use of a geostatistical model. Second, the cornfields are sampled in different corn production areas throughout the watershed using a two stage sampling strategy- the sampling exercise is replicated a 100 times. Third, the sample information is used to estimate the corn production function and runoff function for each production area, thereby determining the pollution and productivity types of the production areas. Non-uniform standards that account for the differences in pollution and productivity type are then set to regulate the total nitrogen loading in the river.

The decision problem can be stated from the perspective of a hypothetical planner who seeks to minimize the expected costs of reducing nitrogen pollution loads to the SRB from corn production in the CRW by imposing standards on nitrogen fertilizer applications. The planner's uncertainty is modeled as uncertainty about parameters of corn production function and pollution transport process determining the costs to agricultural producers of regulations on fertilizers. The distributions of the unknown parameters are assumed known to the planner and are modeled as random variables. Alternative combinations of the unknown parameters define alternative states of the world. Alternative states of the world and the (given) probability distribution over them define the planner's information structure. Enhanced information is modeled as changes in information structure.

The choice of the fertilizer standard is made under three different information structures- (1) a basic information structure that had information only on total annual nitrogen loading at the mouth of the Conestoga River, (2) an enhanced information structure that provides information on the attenuated pollution loads for the corn production areas obtained from sampling for environmental characteristics of the production areas, and (3) an integrated information structure that has information on the corn yield and nitrogen pollution load for the corn production areas as obtained from combined sampling of the corn fields for economic characteristics and production areas for environmental characteristics. Each standard is designed to achieve the same environmental target of reducing the pollution load by the same percentage. The goal is to compare how well the different standards (constructed under different information structure) perform in minimizing the abatement costs of pollution while achieving the same environmental goal.

Expected Value of Information (EVOI), of environmental sampling and of integrated economic and environmental sampling, is modeled as the savings in the cost of enforcement of the standards relative to the case of standards designed under the basic information structure. The effort to sample for information is expended once. However, the information obtained will be used in successive periods, much after the period in which it was collected. To account of the successive use value of the information, the analysis assumes steady state, and measures the Expected Value of Information (EVOI) as the sum of the discounted savings in cost for infinite periods.

3.3. Overview of EVOI Theory and Applications

Value of Information (VOI) analysis extends decision analysis to evaluate the benefits of collecting additional information to reduce or eliminate uncertainty in a specific decision-making context. In an expected utility maximization framework, VOI represents the difference between the expected utility of the optimal action given new information and the expected utility of the optimal action given information available prior to collecting additional information. Raiffa and Schlaifer first introduced the concepts of VOI analysis in their seminal book, *Applied Statistical Decision Theory (Raiffa and Schlaifer, 1961)*.

The expected value of perfect information (EVPI) is mathematically defined as shown in Equation (3.a):

(3.a) $\qquad \text{EVPI} = \text{E}\{\max_a \text{U}(a,s)\} - \max_a \text{E}\{\text{U}(a,s)\}$

where $\text{E}\{\max_a \text{U}(a,s)\}$ represents the expected utility under perfect information (i.e., for each possible value of the uncertain input, *s*, the DM takes an action, *a*, that maximizes utility) and $\max_a \text{E}\{\text{U}(a,s)\}$ represents the expected utility under prior information (i.e., the DM chooses the action that yields the highest expected utility without additional information). The first term in Equation (3.a) therefore represents the weighted average of the utility associated with taking optimal action for all possible values of s over the prior belief about the likelihood of s. The second term in the same equation represents the expected utility from taking an action that yields the highest expected utility.

The partial EVPI or Expected Value of Perfect X information (EVPXI-where X represents a particular uncertain model input) represents the difference between the expected utility from taking the optimal action based on the revelation of the exact value of X and the expected utility from the optimal decision given only the prior information on X (Brand and Small, 1995; Thompson and Graham, 1996). EVPXI provides a useful measure for determining the relative importance of resolving uncertainty between inputs. In the case of two uncertain inputs x and y, Equation (3.b) gives the EVPI about x:

(3.b) $$\mathrm{EVPXI} = \int_x [\max_a \int_y u(a,x,y) f(y \mid x) dy] f(x) dx - \max_a [\int_y \int_x u(a,x,y) f(x,y) dx dy]$$

where $u(a, x, y)$ equals the utility of the DM, $f(y \mid x)$ gives the prior conditional probability of y given x, $f(x)$ represents the prior probability of x, and $f(x, y)$ equals the prior joint distribution of x and y. EVPXI thus becomes the difference between the expected utility from taking the optimal action based on the revelation of the exact value of one uncertain input, x, and the expected utility from the optimal decision given only the prior information.

Since EVPXI provides a useful measure for determining the relative importance of resolving uncertainty of individual uncertain inputs (or more broadly, combinations of inputs), Felli and Hazen proposed its use as the ideal measure for sensitivity analysis in decision analytic problems (Felli and Hazen, 1998; Felli and Hazen, 1999).

The sum of EVPXI from all sources of uncertainty does not necessarily sum to the total EVPI for resolving all uncertainties simultaneously, even for independent model inputs and particularly for inputs with dependent uncertainties- this nonadditivity property explains why EVPXI does not necessarily yield the EVPI, excepting a few limited cases (Howard, 1967; Howard, 1967; Samson, Wirth et al., 1989; Thompson and Graham, 1996). The nonadditivity property also makes it impossible to do the reverse, i.e. estimate EVPXI from EVPI estimates.

Decision analysts also quickly recognized the impossibility of obtaining perfect information in most cases, and consequently, the expected value of sample information (EVSI) or the expected value of imperfect information (EVII) became the more relevant measure of information value in decision making. The EVSI represents the difference between the expected utility under imperfect information (i.e., for each possible value of sample information, t, the DM takes an action, a, that maximizes utility) and the expected utility under prior information (i.e., the DM chooses the action that yields the highest expected utility without additional information):

(3.c) $$\text{EVSI} = \text{EVII} = E_t[\max_a E_{s|t}\{U(a,s)\}] - \max_a E_s\{U(a,s)\}.$$

Calculating EVSI uses a Bayesian preposterior analysis since it requires making a decision before the collection of information and knowledge of the sample outcome. Thus, it requires constructing posterior probabilities for all possible values of experimental results, finding the expected utility for taking the optimal action for each experimental result and taking a weighted average of the resulting utility values over the prior belief about the likelihood of each result. Bayesian updating of the probability of *s* for all possible sample information, *t*, begins with computing the posterior probability of *s* given observation *t*:

(3.d.1) $$p(s \mid t) = \frac{f(s)g(t \mid s)}{h(t)}$$

where $g(t \mid s)$ represents the likelihood function of observing *t* given a state of the world *s*, and $h(t)$ gives the predictive density of *t*: $h(t) = \int_s f(s)g(t \mid s)ds$. Equation (3.d.2) restates EVSI in terms of h(t);

(3.d.2) $$\text{EVSI} = \int_t \underset{a}{\text{Max}}[\int_s u(a,s)p(s \mid t)ds]h(t)dt - \underset{a}{\text{Max}}[\int_s u(a,s)f(s)ds]$$

EVSI represents the difference between the expected utility of taking the optimal action based on the posterior probability of *s* given experimental information *t*, and the expected utility from taking the optimal decision given only the prior information about *s*. Analysts could similarly focus on estimating the expected value of sample X information (EVSXI). The EVPI represents both the simplest calculation and the largest value (i.e., EVPI $\gtrsim$max [EVPXI] and EVPI $\gtrsim$EVSI $\gtrsim$max [EVSXI]), and therefore it often serves as a useful upper bound for the value of any additional information in any particular decision. However, as noted by (Yokota and Thompson, 2004), even the EVPI may underestimate the true societal value of perfect information since positive externalities from information collection may exist (i.e., additional decisions not directly modeled that may be improved from the information collected). Furthermore, the authors note, that collecting additional information can lead to surprises in some cases where the information reveals incorrect basic assumptions (e.g., when observing input values outside the bounds of prior belief) (Hammitt, 1995; Hammitt and Shlyakhter, 1999). Nonetheless, the thumb rule that is often suggested is this: if the cost of collecting imperfect information exceeds the EVPI, then the DM should not invest in the proposed information collection strategy because collecting the information implies a net decrease in welfare.

Yokota and Thompson offer many insights on conducting VOI analyses based on their review of VOI applications in health risk management decisions and in environmental health risk management decisions (Yokota and Thompson, 2004; Yokota and Thompson, 2004). Even setting up a very simple VOI problem requires analysts to model the available set of actions, prior beliefs about the uncertain inputs and about the accuracy of the information collected (characterized using probability distributions like discrete sets of value-probability pairs, parametric distribution functions, empirical distribution functions), the consequences of actions given the true value of the uncertain inputs, and the DM's preferences. The analysis must quantify all relevant consequences of actions from the perspective of the DM and value monetary and non-monetary outcomes using a common metric (typically net benefits in dollars in the context of VOI, or in the case of health decision problems, in terms of units of measuring health). Decision tree and influence diagram are most commonly used in representing and solving decision situation as well as associated VOI calculation. Estimation of VOI problem typically involves use of simulation and other numerical approximation methods. The two review papers by the authors survey a great number of peer reviewed papers published before 2001 and performs content analysis to provide great insights into the evolution and future challenges of VOI analysis in health related decision analysis. The authors note that most articles tend to demonstrate the usefulness of VOI as a technique rather than as an application to actual management decision.

The VOI approach as outlined above is representative of the statistical decision theory approach to VOI analysis in context of an uncertain input in closely defined contexts. Repo (1987) provides an excellent overview of all approaches (and their criticisms) to value of information used in economics; the four predominant approaches he cites are (1) statistical decision theory approach, (2) equilibrium theory approach, (3) multidimensional value approach, and (4) cognitive approach. The approaches differ primarily in the notion of the value being studies (value in use versus value in exchange) and whether the value is being studied retrospectively after the states have materialized or ex ante before the states are realized. The statistical decision theory approach has seen the most adoption in recent literature, primarily in areas of health and environmental economics. Lawrence (1999) provides a (more up to date) wider coverage and a broader framework for determining the economic value of information. He formalizes the concepts of information sources, information structures and their informativeness. *Information* is defined as any stimulus that changes a recipient's knowledge (recipient's existing probability distribution over a well described set of states) and results from the receipt and cognitive processing of *message,* from a data source. Message is the final form output from a data source the semantic content of which can be processed by the recipient and incorporated into his or her knowledge. Since the seeker of the information cannot know what the specific message is before committing to the data source and incurring expenses, message is treated as a random variable. The message space **Y**={y} enumerates all potentially receivable messages from the information source. Prior to the receipt of the message, both the state and the messages are random, and most probably interrelated. Then p(x,y), the joint probability distribution defined on **X** x **Y,** gives the probabilistic relationship between the states that might occur and the messages that might be received.

An *information structure* I comprises the message space and the joint measure on messages and states; I={**Y**,p(x,y)}i.e. The information structure describes both the current and the potential states of knowledge about the unknown random variable X (or more than 2 unknown random variables in the case of multiple unknown inputs). Information structure is a good way of representing the different kinds of information that is being sought. Information structures have varying levels of information associated with them- informativeness of a structure can range from no information to perfect information; anything in between is imperfect information. Associated with each information structure is the Value of Information V(I), where

$V(I) = E_y \underset{a}{Max} E_{x|y} U(x,a) - E_x \underset{a}{Max} U(x,a)$, similar to Equation (3.d) or the EVOI of that information structure, and the expected costs of procuring that information (C(I)). The gain from the information structure is the difference between V(I) and C(I)-the optimal information structure among many competing ones is the one for which the gain is maximized. Lawrence reviews case studies for information values and costs till 1999, in all disciplines, many of which are also cited in Yokota and Thomson's review papers.

One area in which EVOI has been particularly useful has been in determining the value of sampling efforts, and in determining optimal sampling strategy (sample size, location etc) for specific problems(Cox, 1999; Pautsch et al., 1999; Wagner, 1999; Back, 2007). Pautsch et. al paper is particularly worthy of mention as it determines the optimal sample size for soil nitrate testing under Variable Rate Technology (VRT) fertlizer program work-the framework used exploits the degree of spatial correlation and variability of soil nirate levels withn the field and bayesian updating of nirate levels at non sampled sites to determine the optimal number of soil samples (Pautsch et al., 1999).

The application of EVOI theory in watershed based approaches to water quality control, is limited to a study that looks at the EVOI of alternative information structures that reduce uncertainty about either the economic benefits of pollution reduction and the costs of control or the nutrient transport process for watershed based water quality management approach (Borisova et al. 2005). The Borisova et al. (2005) and the Pautsch et al. (1999) paper together provides the framework for the EVOI analysis addressed in this essay.

3.4. The Conceptual Model

This section presents the conceptual model for economic value of information in context of the agricultural nonpoint problem. The model formally develops the notion of productivity (or cost) and pollution impact types, and illustrates their relevance to the design of cost effective outcomes. The presentation of the model is followed by a formal definition of the three regulatory strategies that are considered in the analysis, their informational requirements, and a discussion on their relative efficiency in achieving cost effective outcomes.

The cropland in the watershed is divided into m crop production areas for sampling. The production areas differ in their agricultural productivity and runoff potential. The production areas are further divided into n_i independent units, which are referred to as fields. The fields are the units of management in the crop production areas.

Several crops are produced in the watershed, but as noted above, this analysis is simplified by assuming that corn, which is the dominant crop, is the only crop. Corn output is modeled as a function of nitrogen applied to the cropland and the amount of cropland. This treatment abstracts from the other inputs to focus on the key regulatory variable, nitrogen fertilizer, and to simplify computation.

The production from the fields j in area i (i=1,2,….,m, j=1,2,3,…..,n_i), is given by

(3.1) $$Y_{ij} = f(X_{ij}, b_i)A_{ij}$$

where, Y_{ij} is the corn output, X_{ij} is the nitrogen input, b_i is the site (production area) specific parameter used to define the productivity type, f(.) gives the yield per acre, and A_{ij} is the land area of the field. The analysis is further simplified by assuming that the land area is fully utilized, and that fields are of uniform size throughout the watershed. In this case, $A_{ij} = \bar{A}$, for any i and j, where $\bar{A}$ is the uniform field size. The yield functions, f(.), are assumed to be twice continuously differentiable and concave.

Nitrogen applied to the cornfields is not completely utilized by the crops and a proportion of it ends up as nitrogen loadings in the Conestoga River. The amount of nitrogen leaving the field as runoff, referred to as the edge of the field loss, is assumed to be an increasing function of the nitrogen application. It is expressed for field j in crop production area i as Equation (3.2).

$$(3.2) \qquad r_{ij} = r(X_{ij}, \gamma_i)A_{ij}.$$

γ_i is the vector of site-specific nitrogen retention parameters that determine the runoff from any field in corn production area i. The total nitrogen loading in the river from corn producing area i will then be the sum of the runoffs from all the cornfields in corn producing area i and is given by Equation (3.3).

$$(3.3) \qquad l_i = \sum_{j}^{n_i} r_{ij}$$

l_i denotes the amount of nitrogen that enters the stream from the corn producing area i. Nitrogen dissipitation occurs during transport through the streams. The farther away is the entry point of l_i into the river from the mouth of the river in the watershed, the less will be its impact on the total nitrogen loading (L), measured at the mouth of the main stem of the watershed i.e. upstream locations contribute less to nitrogen loadings than downstream locations. Let θ_i denote the attenuation coefficient. θ_i represents the portion of l_i that is lost during transportation in the streams. θ_i varies proportionately with the distance (along the stream) of crop production area i from the mouth of the river. The total nitrogen loading (L) at the mouth of the watershed is the sum of the attenuated loads, $(1-\theta_i)l_i$, from the m corn producing areas and is given by Equation (3.4).

$$L = \sum_{i=1}^{m}(1-\theta_i)l_i \tag{3.4}$$

Together with γ_i, θ_i determine the pollution impact type of the cornfield j in crop production area i. A high value of γ_i along with a high value of θ_i implies that the crop production area will contribute very little to the total nitrogen loading in the river-high γ_i results in low edge of field loading that is greatly dissipated during transport due to high θ_i resulting in the corn production area being a low pollution impact type. On the other hand, a low value of γ_i along with a low value of θ_i would imply that the crop production area will be a high pollution impact type - low values result in large edge of field loading and small dissipation during transport, resulting in large net loadings to the total nitrogen loading in the river.

The pollution policy targets a α % reduction in L. Let the targeted load be denoted by $T = (1-\alpha)L$. To obtain the least cost solution, the total benefits from corn production (profits in this case) are maximized subject to the environmental constraint. The profit from the jth field in the ith corn production area is

$$\pi_{ij}(X_{ij}, b_i, P, w) = [P.\,f(X_{ij}, b_i) - w.X_{ij})]\overline{A} \tag{3.5}$$

where, P is the corn price per bushel and w is the price of nitrogen fertilizer per pound. The profit maximizing level of fertilizer without regulation satisfies the first order condition,

$$(3.6) \qquad \frac{\partial \pi_{ij}}{\partial X_{ij}} = [P\frac{\partial f}{\partial X_{ij}} - w]\overline{A} = 0$$

Let $X_{ij}^{*}(P,w)$ denote the profit maximizing fertilizer level and π^{*}_{ij} denote the maximum profit. The interest in this study lies in the costs of reducing fertilizers below profit maximizing level, assuming that farmers are profit maximizers. The cost of reducing fertilizer use by regulation is given by

$$(3.7) \qquad C_{ij}(X_{ij}, b_{ij}, P, w) = \pi^{*}_{ij} - \pi_{ij}(X_{ij}, b_{ij}, p, w) \text{ where } X_{ij} \leq X^{*}_{ij}(P, w)$$

The marginal cost of reduction in fertilizer use is then

$$(3.8) \qquad \frac{\partial C_{ij}}{\partial a_{ij}} = -[P\frac{\partial f}{\partial X_{ij}} - w]\overline{A} \text{ where } a_{ij} = X^{*}_{ij} - X_{ij}$$

The decision problem for the water quality manager is to minimize the costs of fertilizer reduction that is required to meet the exogenously specified pollution constraint. The cost minimization problem can be written as,

$$\min_{X_{ij}} \qquad \sum_{i}^{m}\sum_{j}^{n_i} C_{ij}(X_{ij}, b_i, P, w)$$

$$\text{subject to} \qquad \sum_{i}(1-\theta_i)\sum_{j}^{n_i} r_{ij}(X_{ij}, \gamma_i)A_{ij} \leq T$$

The Lagrangian equation corresponding to the minimization problem is given by equation (3.9)

$$(3.9) \qquad Z = \sum_{i}^{m}\sum_{j}^{n_i} C_{ij}(X_{ij}, b_i, P, w) + \lambda[\sum_{i}(1-\theta_i)\sum_{j}^{n_i} r_{ij}(X_{ij}, \gamma_i)Aij - T\,]$$

λ in equation (6) is the Lagrangian multiplier. The Kuhn- Tucker first order conditions corresponding to the maximization problem is given by equation (3.10-3.11).

$$(3.10) \quad \frac{\partial Z}{\partial a_{ij}} = P\frac{\partial Y_{ji}}{\partial X_{ji}} - w - \lambda(1-\theta_i)\frac{\partial r_{ij}}{\partial X_{ij}} \le 0; \qquad a_{ij} \ge 0; \qquad \left(\frac{\partial Z}{\partial a_{ij}}\right)a_{ij} = 0;$$

$$(3.11) \quad \frac{\partial Z}{\partial \lambda} = T - \sum_{i}(1-\theta_i)\sum_{i} r_{ij}(X_{ij}, \gamma_i) \ge 0; \qquad \lambda \ge 0; \qquad \left(\frac{\partial Z}{\partial \lambda}\right)\lambda = 0;$$

$$\forall i = 1,2,...m\,, \quad \forall j = 1,2,....,n_i$$

Assuming an interior solution, and using (3.10-3.11), we obtain equation (3.12).

$$(3.12) \qquad \frac{P\dfrac{\partial f_{ij}}{\partial a_{ij}} - w}{(1-\theta_i)\dfrac{\partial r_{ij}}{\partial a_{ij}}} = \lambda = \frac{\dfrac{\partial C_{ij}}{\partial a_{ij}}}{\dfrac{\partial L}{\partial a_{ij}}} \qquad \forall i, j$$

The numerator on the LHS of λ in 3.12 represents the profit foregone at the margin due to reduced fertilizer use for the field j in corn production area i. It is the marginal cost of reduced nitrogen fertilizer input, which is the numerator on the RHS of λ in 3.12. The denominator on the LHS of λ in 3.12 represents the reduction in runoffs at the margin as a result of reduced fertilizer application. It is the marginal reduction in total nutrient load arising from a reduction in fertilizer use in the j^{th} field in corn production area i. Together the numerator and the denominator define the marginal cost of abatement of nutrient reduction in the river for field j in production area i. The first order condition says that in the least cost solution, the marginal costs of abatement have to be equal for all fields in the watershed, provided fertilizer use is positive. Deviation from this condition means that costs are not being minimized.

Figure 3-1 is a graphical illustration of the least cost solution, for two cornfields case. The figure is in two parts, (A) and (B). O_1 and O_2 denote the axes origins of the two cornfields. l_1 and l_2 denote the pollution loadings from fertilizer application for the two fields respectively in part (B) , the with the values of θ and γ determining the location of the curves on the graph. The profit maximizing (unregulated) fertilizer input quantity for the two fields are X_1^* and X_2^*, and the corresponding nitrogen loading amount for the two field are l_1^* and l_2^*, which adds to a sum that exceeds the targeted in stream load quantity, T, which is the length of the axis in (B). The nitrogen loads for both fields need to be reduced such that T is achieved. To decide on the cost effective allocation of pollution reduction for each cornfield, we look at the cost of pollution reduction for each unit of reduction for both fields. In figure 3.1 (A), MAC_1 and MAC_2 represent the Marginal Abatement Cost curves for field 1 and 2 respectively. The MAC curves slope upward from right to left for field 1 and from left to right for field2; marginal costs of pollution reduction commonly increases with the amount controlled. Productivity and pollution types of the two fields determine the relative location of the two curves. Point E, where the two curves intersect, is the point where the marginal cost of pollution reduction is equal for the field. To the left of E, it is more efficient more field 2 to reduce the loading, as its cost for doing so is less than the cost incurred by field 1 for reducing it. Similarly, for points to the right of E, the costs for reduction are less for field1 than field 2-it is more efficient for field 2 to reduce the load. $l^{\wedge}$ is the efficient allocation of load for both fields, and the fertilizer standards that will achieve this load allocation are $\hat{X}_1$ and $\hat{X}_2$ for fields 1 and 2 respectively.

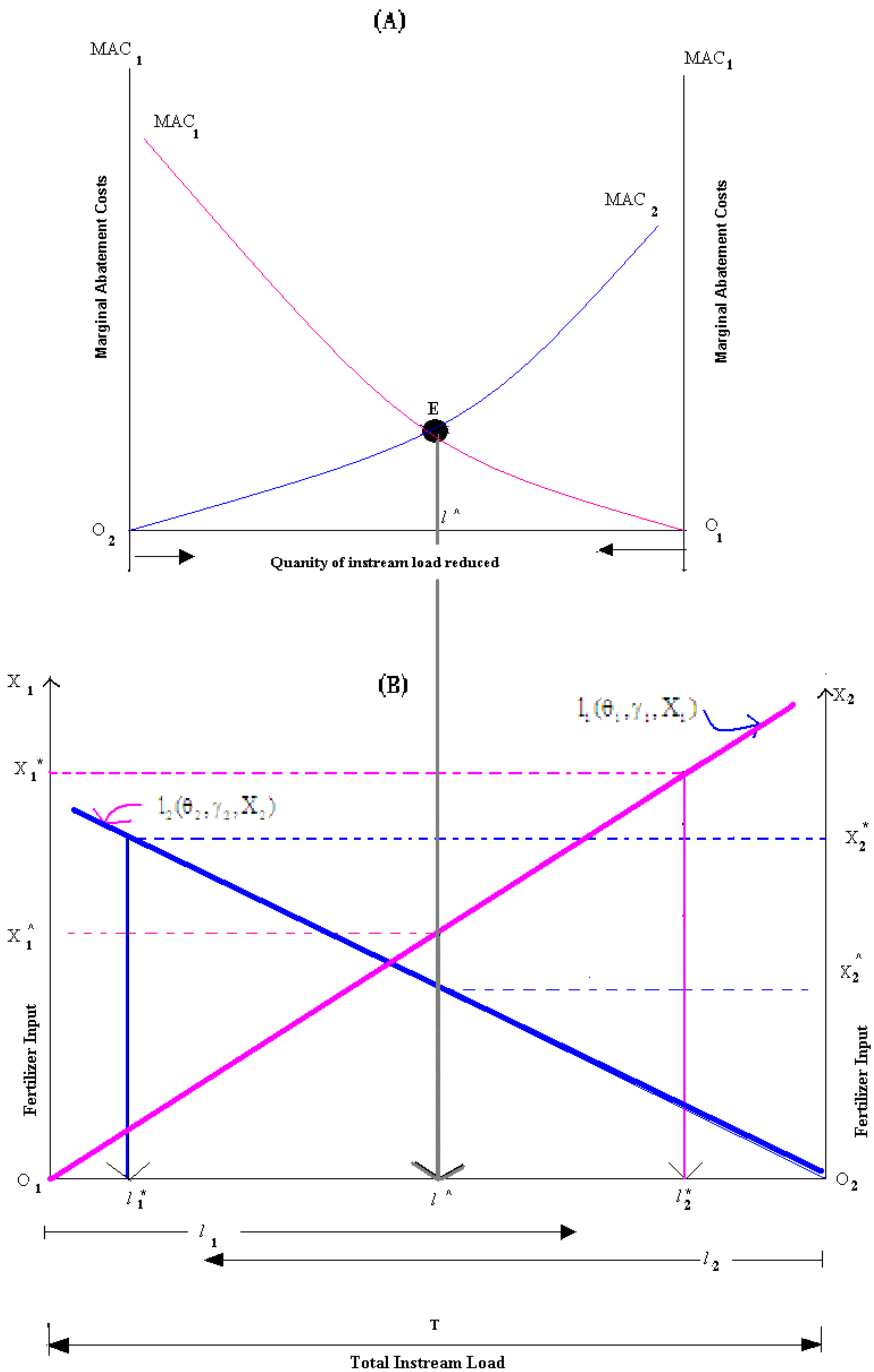

Figure 3-1: Least Cost Solution for reducing pollution load

Figures 3-2 and 3-3 illustrate how differences in pollution and productivity types affect the location of the MAC curves, and therefore the cost effective load reduction allocations. In both figures, MAC_1 is held fixed and variations are showed for MAC_2 curve. If field 2 is exactly like field 1 in both pollution and productivity, then MAC_2 will be the exactly same as MAC_1, and the solution would be equal amounts of load reduction for both. This is denoted by point E on the graphs. This would be the ideal case for levying uniform standards. But in reality, fields are heterogeneous in both pollution and productivity types. Figure 3-2 represents the case where both fields are homogenous in their pollution type but productivity of field 2 is greater than that of field 1. The MAC for field 2 will be higher than MAC for field 1 for all units of load reduction; the MAC curve will be at MAC_2(HPR) for field 2 and the cost effective solution is E_{HPR}. Field 1, which has the lower cost of abatement than field 2 is required to abate more of the load. This is the case where the standards sets for field 1 would be greater than the standards set for field 2. Alternatively if field 2 was lower in productivity than field 1 while contributing same pollution as field 1, then it MAC for abatement would be located lower at MAC_2 (LPR), and the cost effective load allocation E_{LPR} would require field 2 to abate more than field 1. The standards designed for field 2 would then exceed that of field 1.

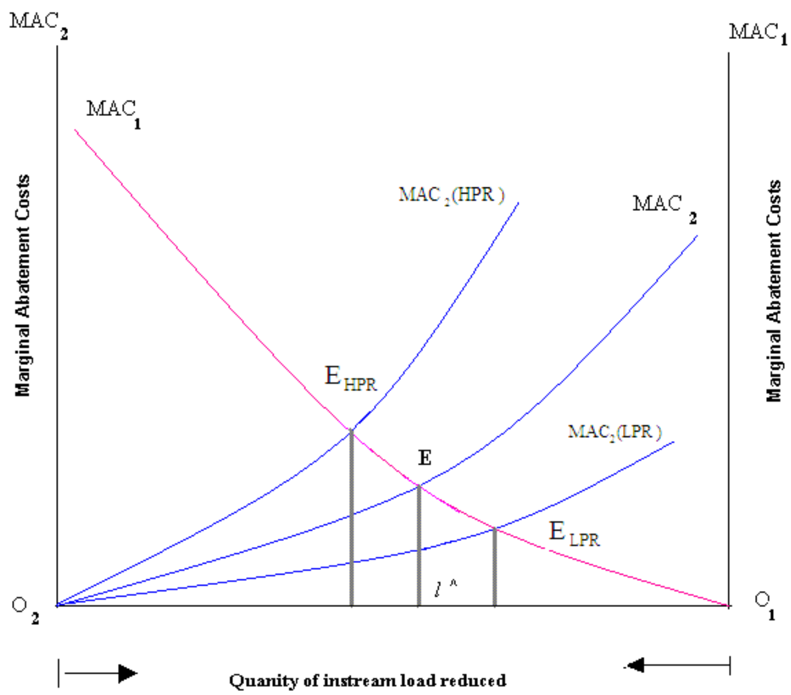

Figure 3-2 Least cost solution under productivity type heterogeneity

If both fields are homogenous in their productivity, but differ in their pollution type, the locations of the MAC curves (relative to the location of the MAC curves when both fields are homogenous in all types) is reversed- Figure 3-3 illustrates the case where the field are homogenous in their productivity but differ in their pollution types. If field 2 is more polluting than field 1, then the resultant MAC curve is MAC_2(HPO) –field 2 which produces more pollution can abate more than field 1 for the same additional unit cost than field 1. Correspondingly, the least cost solution requires field 2 to abate more than field1. Alternatively, if field 2 is less polluting than field 1, then the relevant MAC curve is MAC_2 (LPO) and field 1 is required to abate more than field2. Choice of standards that will achieve the least cost solution will vary accordingly. At $E_{LPO,}$ field 1 will face stricter standards than field 2 as it can abate at lesser cost than field 2. At E_{HPO}, standards are reversed for the two fields.

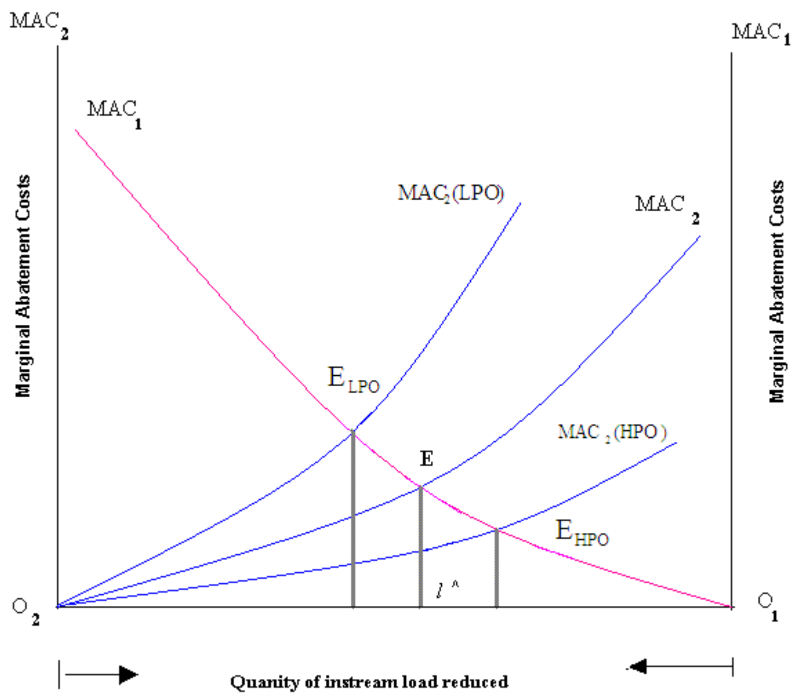

Figure3-3 Least cost solution under pollution type heterogeneity

3.5 Imperfect Information and the Choice of Standards

As established in the previous section, a cost effective policy minimizes the total abatement costs for society for a given pollution load reduction, and the way to achieve the least cost solution is to equate the marginal abatement costs for all sources of pollution. Implicit in the least cost condition is the requirement of having perfect information on the MAC for all pollution sources involved. For watershed water quality managers, the condition requires having perfect information on all parameters that determine the cost of pollution reduction; this includes perfect information on (1) corn productivity parameter b, and (2) on pollution loading and transport parameters θ, and γ , for all the m corn production areas in the watershed. Water quality managers usually have no information or very little information on one or all of the relevant parameters. Table 3-1 lists the information structures that water quality managers can conceivably have when dealing with information on the three parameters, b, θ, and γ. Moving down the table from 1 to 3, each information structure provides additional information to the water quality manager than the previous structure, reducing uncertainty about the three variables.

Table3-1 Information structures (I)

Structure	Name	Description
1	Baseline Information	No information on any parameters
2	Environmental Information	Perfect Information on attenuation coefficient θ, others uncertain
3	Integrated Environmental and Economic Information	Imperfect information on pollution transport parameters θ, γ, and imperfect information on cost parameter b

As established earlier, the tradeoff in non-point pollution control is between information and efficiency in policy design. The more information that is available to the water quality manager, the better the manager is at designing control instruments that achieve the least cost solution. The following paragraphs explore the design of quantity control or standards under the three information structures and how the standards achieved perform in terms of cost effectiveness. This analysis focuses on standards as the regulatory strategy for two reasons. Firstly, the analysis uses the case study of non point source water pollution, which is inherently characterized by the problems associated with monitoring emission by source. Due to the impossibility of monitoring non point pollution by source, indirect instruments like input taxes and standards are suggested for controlling non-point pollution as opposed to direct instruments levied on emissions under point source pollution (Griffin and Bromley, 1982; Shortle and Dunn, 1986; Shortle and Horan, 2003). Secondly, in situations characterized by simultaneous uncertainty in benefits and costs with positive statistical dependence between them, it is quantity instruments like standards emerge efficient compared to price instruments like taxes; situations characterized by positive correlation between uncertain benefits and costs are more likely to occur in environmental economics (Stavins, 1996).

There are three different types of nitrogen standards that are considered in the analysis- (1) uniform standards ($\mathbf{s_1}$) chosen under information structure 1, (2) standards that equalizes per unit area net nitrogen loading from the m corn production, chosen under information structure 2, (3) standards that maximize the profits of corn production from the m corn producing areas, chosen under information structure 3. All three standards are designed to achieve the same environmental target of T net nitrogen loading in the watershed. The standards are corn production area specific limits that are set on the amount of fertilizer applied to corn.

The amount of information that the DM has under information structure 1 is minimal. The water quality manager who regulates the nitrogen input of the cornfields does not have any information either on b_i, θ_i or γ_i , and has no way of differentiating among the cornfields in the different production areas. The DM's only response it to treat all sources uniformly and set standards that are homogenous for all corn production areas. The DM however has no way of knowing the level at which the uniform standards s_1 should be set such that it achieves the target Load of T. Mathematically, the uniform standard (**s_1**) ($s_{1ij} = s_1 \forall i, j$) that will achieve the targeted load T (assuming no change in area in corn production or other parameters due to changes in cropping practices etc.) must satisfy Equation (3.13).

(3.13) $$T = \sum_j (1-\theta_j) \sum_i^{m_j} r_{ji}(s_1, \gamma_j) A_{ji}$$

However, under information structure 1 the DM does not have the information required to arrive at correct level of the standards. While setting uniform standards, regulator only knows what the total loading (L) in the watershed is and what he wants it to be (T). Under the circumstance, the DM picks an arbitrary number and sets it as the uniform standard for all. The DM then waits to see if the target load is achieved or not, and keeps adjusting the number till the target is achieved. The analysis abstracts away from modeling the DM's behavior and assumes the equilibrium choice, arrived at by trial and error-i.e. Repeatedly adjusting the level of **s_1** till T is achieved, as the level for uniform standards. Obviously there are costs to persisting with the baseline information structure and not enhancing it, but the costs of the errors are not included in the EVOI computation i.e. the costs of mistakes avoided represents a value of enhanced information but that is not included in EVOI measure.

Under information structure 2 the DM has imperfect information on one of the parameters (the attenuation coefficient) that determine the pollution type of the corn production areas. The information is made available by sampling the corn production areas for variables (like total loading l_i from corn production area i and distance of the entry point of loadings in the streams from the mouth of the watershed) that allows estimation of the value of θ_i. Sampling for information on pollution types, i.e. for information on θ_i, is referred to as 'sampling the environmental information'.

Information structure 2 provides the DM with the information that enables design of heterogeneous standards that account for the differences in the pollution impact types of the corn producing areas. Under the second type of standard, the regulator sets heterogeneous standards (**s_2**) such that the net nitrogen delivered to the mouth of the watershed, $(1-\theta_i)l_i$, per unit area from each corn production areas is a constant, say ω. The standards (s_{2i}) are specific to each corn production area i and are imposed on all cornfields within i, i.e. $s_{2ij} = s_{2i}, \forall j \in i$. The level of standard $s_{2\mathbf{i}}$ that will achieve the pollution target T is the solution of Equations (3.14) and (3.15).

$$\text{(3.14)} \qquad \frac{(1-\theta_i)l_i}{\sum_j^{n_i} A_{ij}} = \frac{(1-\theta_i)\sum_j^{n_i} r_{ij}(s_{2i}, \gamma_i)A_{ij}}{\sum_i^{n_j} A_{ij}} = \omega \forall j, i$$

(3.15) $$\omega\sum_i\sum_j A_{ij} = T$$

Under this standard system, the fields are not penalized uniformly as in the case of uniform standards but to the extent that they contribute to the total nitrogen loading in the watershed. Without access to the information on pollution types, the regulator will have to resort to designing uniform standards as described previously.

Under the third kind of standards, made possible by information structure 2, the DM sets standards (**s_3**) that maximize the profits from corn production while achieving the pollution target (T). The standards are defined separately (s_{3i}) for each of corn producing area i and are imposed for all cornfields j within i, i.e. $s_{3ij} = s_{3i}, \forall j \in i$. The standard s_{3j} that achieves the pollution target is the solution to the following optimization problem.

$$\underset{s_{3i}}{\text{Max}} \quad \sum_i\sum_j \; (P\, f_{ij}(s_{3i}, b_i) - ws_{3i})A_{ij}$$

$$\text{subject to} \quad \sum_i (1-\theta_i)l_i = \sum_i (1-\theta_i)\sum_j^{m_i} r_{ij}(s_{3i}, \gamma_i)A_{ij} \leq T$$

For determining the level of **s_3**, information is required both on the productivity type and the pollution type of the m corn production areas. The DM requires information both on the economics of corn production (knowledge of parameter b_i) and net contribution to pollution (knowledge of parameter θ_i or γ_i) for the i areas for designing **s_3**- information on the parameters θ_i or γ_i are the contents of information structure 3. The DM obtains the information on the productivity type of corn producing area i by estimating the corn yield function ($f \;(X_{ij}, b_i)$ for that area using data obtained from sampling for corn yield and nitrogen fertilizer application in the cornfields within corn production area i. Similarly the DM obtains information on the pollution impact type (θ_j and γ_j respectively) of the j[th] corn producing areas by (1) sampling for the dissipation in l_i along the river and (2) by estimating the runoff function, $r\ (X_{ij}, \gamma_i)$, using data obtained from sampling of edge of field runoff and nitrogen application at the field level. The joint sampling of the cornfields for economic information on corn productivity and environmental information on pollution impacts of the corn production areas is referred to as sampling for 'integrated economic and environmental information' in the analysis.

The maximization problem for achieving the third kind of standard is identical to the optimization problem that yields the least cost solution. For the case when the regulator has perfect information regarding the costs and pollution types of all firms, the standards s_3 will achieve the least cost condition. Since standards in this analysis will be designed based on imperfect information available from sampling, the standards (s_3), will not achieve the least cost solution perfectly.

The relative efficiency of the three kinds of standards in terms of cost effectiveness is presented next. Figure 3-4 illustrates the performance of the three standards in minimizing the costs of abatement. In Figure 3-4, the two cornfields, denoted by 1 and 2 differ both in their cost and pollution types, and therefore have very different MAC curves. The least cost solution is obtained at E, where the two MAC curves intersect. The shaded area in Figure 3-4 represents the total cost of abatement (TAC) corresponding to the least cost solution E. $l(s_1)$ denotes the allocation of load between the two field corresponding to uniform standards. The TAC corresponding to this allocation is the shaded area plus area (a+b+c). $l(s_2)$ denotes the allocation of load between the two field corresponding to standards s_2 designed using environmental information alone. The TAC corresponding to this allocation is the shaded area plus area (b+c). $l(s_3)$ denotes the allocation of load between the two field corresponding to standards s_3. The TAC corresponding to this allocation is the shaded area plus area (c). The TAC is least for the standards that were designed using both economical and environmental information.

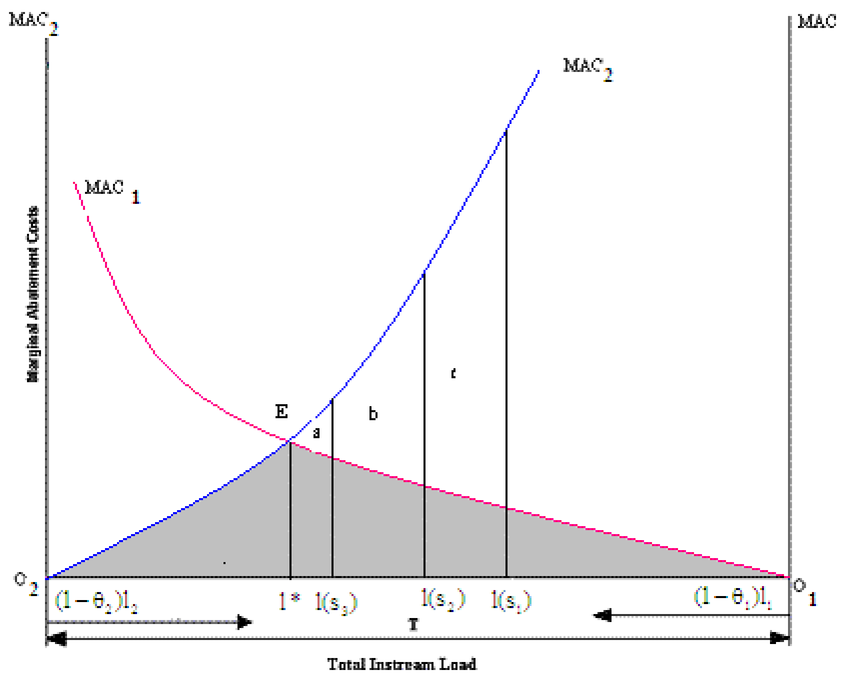

Figure 3-4: Cost minimizing efficiency of the three standards

3.6 EVOI of Alternative Sampling Strategies

The EVOI of environmental sampling and integrated sampling of the economy and environment is now examined. As stated earlier, EVOI represents the expected value of obtaining imperfect information (sample information) about individual or combination of the parameters b, θ, and γ. The baseline profits (Π) is the sum of the profits (π_{ji}) of the corn-producing field in the watershed in the absence of any standards, $\Pi = \sum_{i}^{m}\sum_{j}^{n_i}\pi_{ij}$. Under the baseline, farmers are assumed to apply profit-maximizing amounts of fertilizer ($\overset{*}{x}_{ij}$) on the cornfields. Therefore, $\Pi = \sum_{i}\sum_{j}^{n_i}\pi_{ij}(\overset{*}{x}_{ji}, b_i, P, w)$, where P is the price of corn and w is the price of the nitrogen fertilizer respectively.

The fields experience a reduction in profits when standards are imposed on fertilizer application if the standards imposed $s_{qij} < \overset{*}{x}_{ij}$, for the three information structures $q = 1,2,3$. Let Πs_q denote the total profits from all the cornfields in the watershed when their fertilizer input is restricted by standard s_q, $\Pi s_q = \sum_{i}\sum_{j}^{n_i}\pi_{ij}(s_{qij}, b_i, A_{ij}, P, w)$. Then R_q , $R_q = \Pi - \Pi s_q$, represent the reduction in profits owing to the standards imposition. R_q reflects the cost of enforcing pollution control with standards s_q.

Under information structure 1 or baseline information, the DM, as established in the previous section, opts to impose uniform standards. The cost of enforcing pollution control under uniform standards is given by

$$(3.16) \qquad R_1 = \Pi - \Pi s_1 = \sum_{i}\sum_{j}^{n_i}[\pi_{ij}^{*}(x_{ij}, b_i, P, w) - \pi_{ij}(s_1, b_i, P, w)]$$

Under information structure 2, the DM has access to imperfect information on θ_i and has the ability to define standards $\mathbf{s_2}$**,** such that net nitrogen delivered per unit area from each corn production area to the mouth of the watershed is equal for all corn production areas. The cost of enforcing pollution control under heterogeneous standards that accounts for pollution contribution is given by

$$(3.17) \qquad R_2 = \Pi - \Pi s_2 = \sum_i \sum_j^{n_i} [\pi^*_{ij}(x_{ij}, b_i, P, w) - \pi_{ij}(s_{2i}(\theta_i), b_i, P, w)]$$

If the additional information on θ_i obtained from environmental sampling does have value, then it should result in choice of standards that does a better job of minimizing the societal costs of pollution control, i.e. $R_1 > R_2$. EVOI of environmental sampling is therefore modeled as the cost savings of the standards $\mathbf{s_2}$**,** relative to the case of uniform standards (s_1) and is given by equation (3.18)

$$(3.18) \qquad \text{EVOI (I=2)} = R_2 - R_1$$

Similarly, EVOI of integrated sampling of the environment and economy is modeled as the savings in cost of standards s_{3i} , relative to the case of uniform standards. The costs of pollution control under information structure 3, where the DM has imperfect information on all three parameters b, θ, and γ is given by (3.19).

$$(3.19) \qquad R_3 = \Pi - \Pi s_3 = \sum_i \sum_j^{n_i} [\pi^*_{ij}(x_{ij}, b_i, P, w) - \pi_{ij}(s_{3i}(b_i, \theta_i, \gamma_i), b_i, P, w)]$$

EVOI of information structure 2 (integrated sampling of the economy and the environment), is then given by (3.20)

$$(3.20) \qquad \text{EVOI (I=3)} = R_3 - R_1$$

It is important to point out here that the information collection via sampling occurs only once. However, the information will be used in all the successive years. The information generated through sampling will continue to be of value with repeated use over the years. The repeated use values need to be factored in the computation of EVOI. The manner in which EVOI measures are defined automatically makes them dependent, and therefore sensitive, on the price of corn and nitrogen fertilizers. Assuming steady state in which the prices do not change, the value of the information (VOI) collected is the sum of the discounted savings in costs for infinite periods. i.e. VOI = $\frac{R_1 - R_q}{1-d}, q = 2,3$, where d=1/(1+r), and r is the rate of discount used for discounting the future.

3.7 The Empirical Model

This section presents the details of the empirical framework used for examining the EVOI of alternative information structures. The Conestoga River Basin watershed, a sub watershed of the Susquehanna River Basic watershed (SRB), is chosen as the case study watershed for the analysis. The agricultural land within the CRW is divided into sub areas, which represent the areas of crop production (corn in this case). GIS-based application of the Generalized Watershed Loading Function (GWLF) simulation model is coupled with weather data and water balance conditions data pertaining to CRW to compute annual nitrogen loadings for the corn production areas in the CRW. Geostatistical models are then used to simulate the processes of corn production and pollution transport for the CRW and the models are calibrated such that the mean values of the simulated loadings aligns with the annual nitrogen loading as established by the GWLF model for the CRW. The EVOI is examined by simulating the results of alternative sampling strategies of simulated cornfields in the CRW. In principal one could have sampled actual cornfields in the watershed, but location information of cornfields on the watershed is not available. The cornfields are simulated in the agricultural area of the CRW using GIS software (ArcView) interface.

3.7.1 Creating the corn production areas

As noted earlier it is the spatial heterogeneity in soil types and distance from the mouth of the river that primarily drives the differences in productivity and pollution types across the watershed. To capture heterogeneity across the agricultural land in the watershed and in terms of corn productivity and nitrogen pollution, the agricultural land in the CRW was divided into sub areas, which were termed as corn production areas. Using a GIS software (ArcView) interface, land use data[5] was used to identify areas in the CRW that were primarily agricultural lands. Using the classification of agricultural capability classes and data on soil type, sub areas (irregular polygons) within the agricultural land of the CRW were created to represent areas of corn production. Agricultural capability classification is a rating system for soils developed by The National Cooperative Soil Survey at the National Resource Conservation Service (NRCS). There are eight classes in all but only the top four classes are suitable for agriculture. A query that resulted in selection of areas in the CRW where agricultural capability was indicated to lie between 1 and 4 was used to generate the polygons. The exercise resulted in the creation of 43 polygons in the GIS software ArcView. Therefore there are 43 corn

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[5] All data for the Conestoga watershed and shapefiles for the GIS analysis is provided by Dr. Barry Evans, Director, PSIE GIS Support Center, (814) 865-3357, bme1@psu.edu

production areas identified within the CRW for the analysis, i.e. i=1, 2,…..,43. Figure 3-5 shows the map of the corn production areas in the Conestoga watershed. Most of the sub areas belong to capability class 2, denote by green on the Figure 3-5. There are only 3 sheds that are of capability class 4, indicated by dark brown in Figure 3-5. It is not surprising that most sheds belong to either capability class 1 and 2 as the Conestoga is a rich agricultural area. Together there are 8, 25, 7, and 4 corn production areas corresponding to agricultural capability class 1, 2, 3, and 4.

As per modeling assumption, nitrogen loading in the watershed occurs from corn production in the cornfields that are located in the 43 sub areas. The polygons (production areas) vary in the physical characteristics affecting fertilizer input choices in the cornfields, corn yield levels, Edge of Field (EOF) nitrogen loading to the streams and the total loading to the Conestoga watershed. This translates to differences in the productivity and pollution type of the corn producing areas. The best yield is for agricultural capability class k=1. The yields progressively decrease with k=2, 3, and 4 i.e. mathematically, $Y_{i,k=1} > Y_{i,k=2} > Y_{i,k=3} > Y_{i,k=4}$ for the same nitrogen fertilizer input. The nitrogen runoff is least for soils belonging to agricultural capability class 1 as the high yields of corn uptakes most of the nitrogen applied, leaving little in the soil for runoffs.

GIS-based application of the Generalized Watershed Loading Function (GWLF) simulation model used by the Penn State Institute of the Environment (PSIE), is then coupled with weather data and water balance conditions data pertaining to CRW to compute annual nitrogen loadings for the corn production areas in the CRW. Details of the AVGWLF tool that facilitates the use of GWLF model via ArcView (GIS software) interface can be found at the PSIE website (PSIE, 2005). The GIS software computed the area for each sub area and the estimated travel time from the center of the sub area to the Conestoga outlet. A nitrogen decay rate of 46 % per day was then multiplied to the estimated nitrogen travel time for each sub area to compute the attenuation coefficient for each corn production area. The annual nitrogen loads and the derived attenuation coefficients for the 43 corn production areas in the CRW is listed in Table 3 - 2.

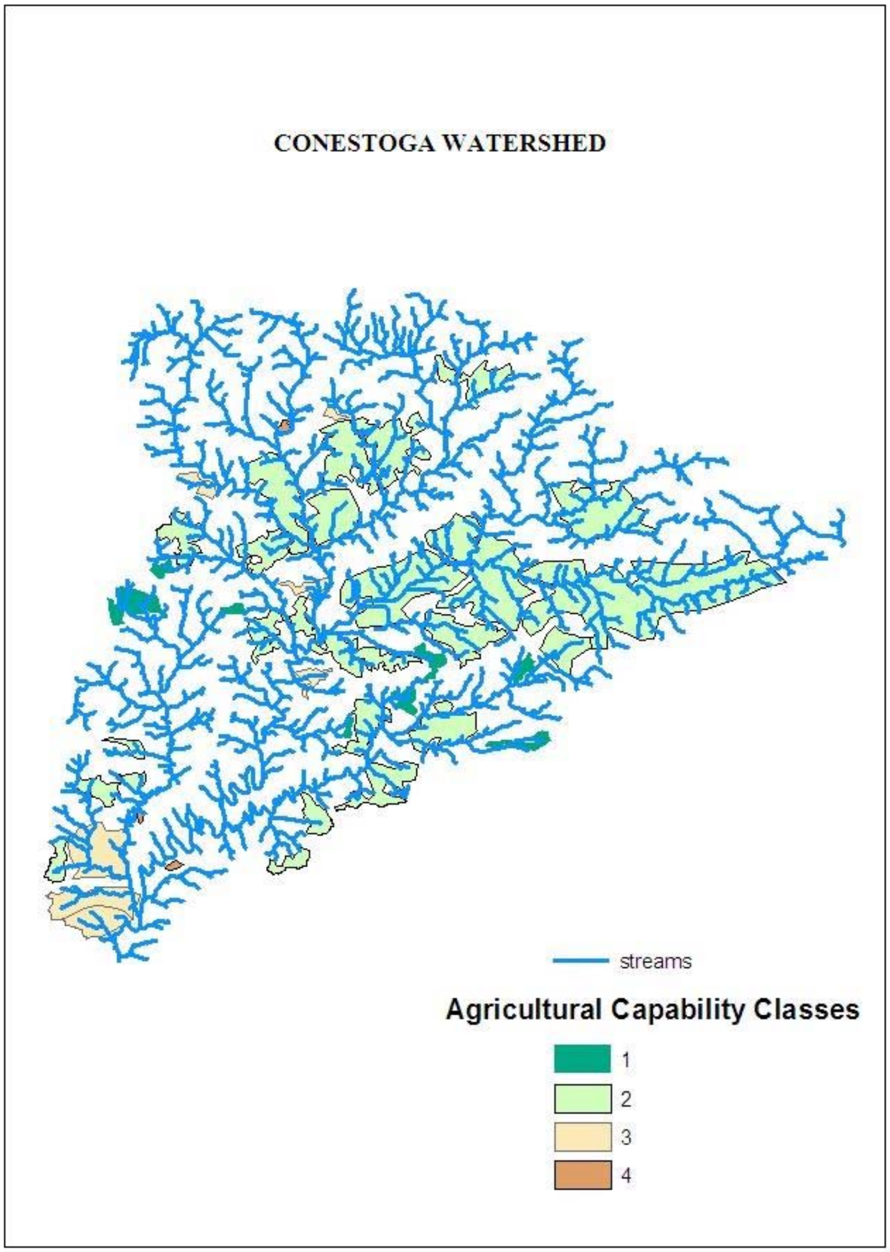

Figure3-5: Map of the polygons (corn producing areas) in the Conestoga Watershed.

Table 3-2 Annual nitrogen loads for the 43 corn production areas in the CRW

Corn Production Area #	Instream Travel Distance(meters)	Nitrogen Attenuation Factor	Annual Nitrogen Loading (KgN/Yr)	Adjusted Annual Nitrogen Loading (KgN/Yr)
1	29357	0.3	14577	10218
2	46763	0.48	1892	987
3	54074	0.55	3195	1432
4	37871	0.39	1905	1169
5	43327	0.44	2029	1133
6	43570	0.45	2538	1405
7	50512	0.52	4893	2372
8	39321	0.4	871	519
9	15526	0.16	7306	6130
10	15025	0.15	4489	3807
11	12119	0.12	5352	4688
12	29642	0.3	5330	3712
13	20403	0.21	4430	3513
14	27390	0.28	7836	5638
15	32553	0.33	8416	5629
16	38274	0.39	9273	5647
17	52657	0.54	17696	8172
18	43533	0.45	7830	4336
19	52432	0.54	15224	7030
20	51654	0.53	35105	16534
21	57611	0.59	30136	12392
22	56452	0.58	32474	13652
23	47200	0.48	16363	8460
24	42919	0.44	4857	2712
25	50695	0.52	11964	5745
26	53523	0.55	90542	40979
27	48758	0.5	54561	27204
28	55371	0.57	25333	11000
29	55585	0.57	72625	31200
30	30390	0.31	14293	9822
31	33759	0.35	3545	2322
32	59904	0.61	1463	568
33	56091	0.58	493	210
34	57461	0.59	1934	795
35	38319	0.39	2455	1495
36	10918	0.11	19572	17411
37	8954	0.09	25851	23473
38	60329	0.62	23110	8865
39	64358	0.66	7409	2535
40	10136	0.11	728	651
41	12219	0.12	778	681
42	42371	0.43	7960	4518
43	3194	0.03	17198	16645

3.7.2 Creating the Cornfields in the Watershed

Shapefiles (format in which the GIS software identifies the location of spatially referenced features) of actual cornfields in the CRW is not available. Shape files of actual farms in the watershed can neither be created, as for propriety reasons, location information on farms are not publicly available. This implies that for the purpose of the analysis, (to be able to sample the fields to estimate the yield function for the corn producing areas), the locations of the cornfield have to be simulated across the Conestoga watershed landscape. The spatial simulation of the cornfields is achieved using the 'Sample' extension provided with (GIS) ArcView 3.2 software. The extension was primarily designed in the software to generate sampling points in a given sampling region, to facilitate geo referenced environmental sampling in disciplines like agriculture, forestry, environmental management etc. The corn production areas (polygons) were input into the program as the sample region and the program was then requested to create sampling points in the polygons subject to a distance criterion. The sampling points generated served as the centroid of the cornfields. The distance criteria required the size of the cornfields to correspond to 52 acres (21 hectares), which is the average size of farms in the Conestoga watershed (LCWA, 2006). The number of fields allotted to each corn production area is proportional to the acreage of the production area. A total of 1288 farms are created by the program and randomly placed across the 43 corn production areas[6]. Figure 3-6 shows the distribution of the centroid of the cornfields across the corn production areas of Conestoga watershed.

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[6] Dr. Steve Graham, GIS Analyst at the Penn State Institute of Environment, is acknowledged for his assistance in creating the population of farms.

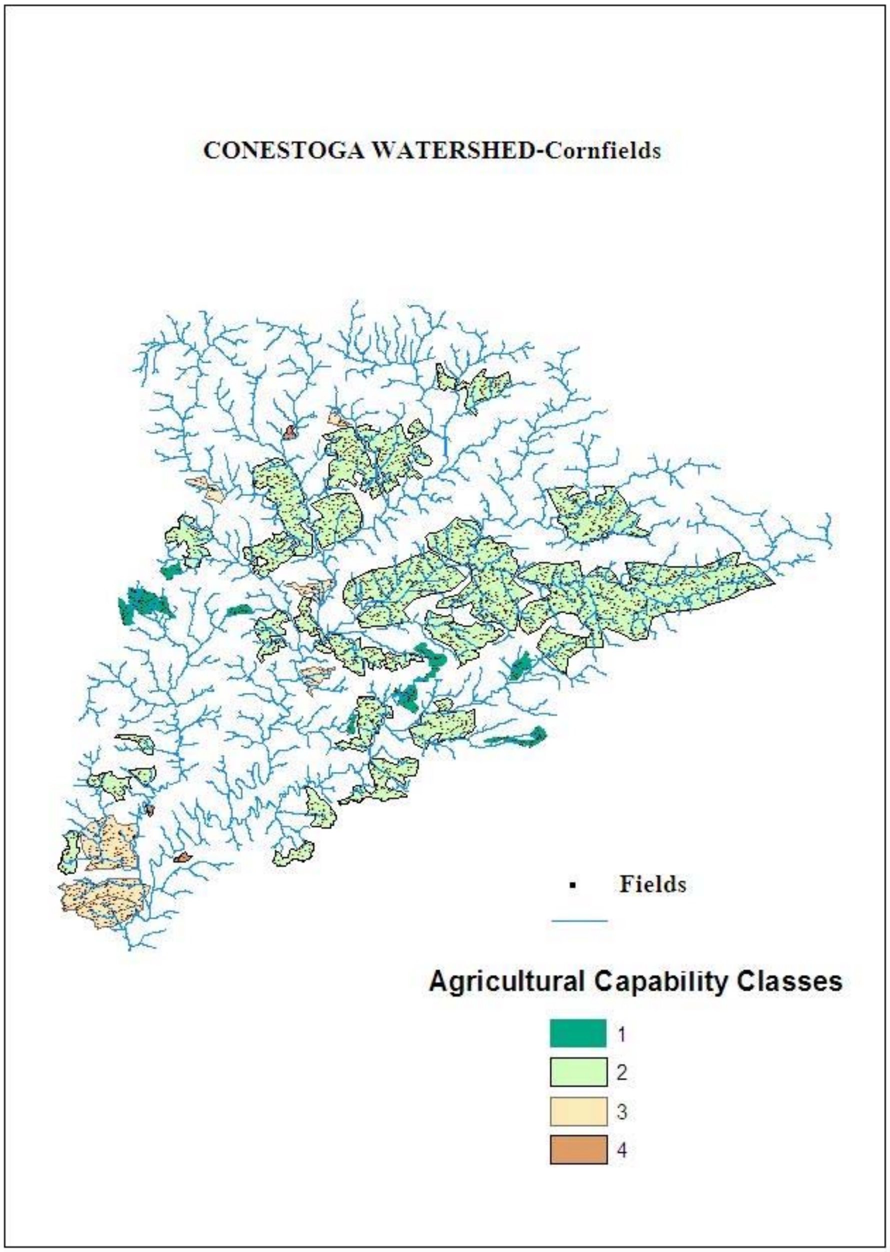

Figure 3-6: Location of the simulated cornfields in the Conestoga watershed.

3.7.3 *Corn Yield Functions*

The production function for corn relates corn yield with the nitrogen fertilizer input. Corn yield for given level of nitrogen input determines the productivity type of the cornfield, which in turn determines the cost type. Sampling for economic information refers to sampling the cornfields for corn yield and fertilizer application data such that the yield function can be estimated. The data from a previous study on corn yield response to nitrogen suggests a maximum bound for yield, beyond which the yield levels off(Fox and Piekielek, 1983). The commonly used mathematical functions in literature for fitting data on yield response to nitrogen fertilizer input are the quadratic and the linear plateau (Fox and Piekielek, 1983; Dillon and Anderson, 1990). Accordingly, a bounded exponential which combining features of both quadratic and the linear plateau, is used in this analysis to model corn yield response to nitrogen fertilizer input. The exponential functions retains the characteristic of the quadratic in the initial increase of corn yield in response to nitrogen fertilizer and differs from the linear plateau in its asymptotic leveling of the yield at the maximum yield value. The yield of corn per unit area for each field j in corn production area is given by the yield function in Equation (3.21). The yield is a function of per unit area nitrogen fertilizer input x_{ij}, and the agricultural capability class of the soil of the cornfield, which is captured by the parameters $\beta_{k0}, \beta_{k1}, \beta_{k2}$.

(3.21) $$Y_{ij} = \beta_{ko} + \beta_{k1}(1 - e^{-\beta_{k2} x_{ij}}), k = 1,2,3, \text{and}, 4$$

3.*7.4 Calibrating the Parameters of the Corn Production Model*

The nitrogen fertilizer yield relationship reported in equation (3.19) is estimated for agricultural capability class 1 (k=1) using secondary data on corn response to nitrogen obtained from experimental sites in Lancaster county, Pennsylvania (Fox and Piekielek 1983). Lancaster County is a major part of the CRW and the soil of the experimental sites in Lancaster County in the Fox and Piekielek (1983) study corresponded to capability class 1, making the data of the experimental sites of Lancaster County the ideal choice for estimating the corn yield function for agricultural capability class 1 in CRW. A Gauss Newton non-linear optimization procedure is used in SAS computer software to estimate the parameters. The estimated values for the parameters of the yield function corresponding to k=1 is reported in Table 3-3. The variance of corn yield as established by the data and estimation procedure is 2.05.

As data for corn yield response to nitrogen relevant to the CRW was available only for sites in Lancaster County, the corn yield function could only be estimated for capability class 1. To establish corn yield response to nitrogen for the remaining three types of soil, we make use of the productivity (yield) aspect that is a consideration in classifying the agricultural capability of soil. The greatest yield, as noted earlier, occurs in soils rated capability class 1, as that is the type of soil most endowed to support agricultural cropping. Soils belonging to capability class 2 tend to have slightly lower yields than that of class 1, while those characterized as classes 3 and 4 tend to have much lower yield than class1. The knowledge that the yields for other capability classes are generally lower than the yield for capability class 1 for any given level of fertilizer input allows us to place some subjective values (relative to the yield of agricultural capability class 1) on the maximum yields of the remaining classes. The maximum yields for k= 2, 3, and 4 is set at 0.9, 0.7, 0.5 respectively of the maximum yield for k=1. β_2 is kept constant but the intercept parameters (β_0, β_1) in equation (3.19) for each class are lowered to match the corresponding maximum yield for that class i.e. the slope of the yield function stays the same for all classes but the levels at which the yield function levels of differs for all the four classes . Table 3-3 lists the resultant parameters of the yield function for the four capability classes.

Table 3-3: Corn yield function parameters for the agricultural capability classes.

Agricultural Capability Class (k)	Yield Function Parameters			Maximum Possible Yield (Y_{max}) in tons	Profit maximizing levels of fertilizer input ($\hat{X}(k)$) in (KgN/hectare)	Per hectare yield^ at the profit maximizing levels of fertilizer input $Y[\hat{X}(k)]$
	β_0	β_1	β_2			
1*	7.62	2.69	0.01	10.11	156.21	9.54
2	6.68	2.42	0.01	9.10	145.63	8.53
3	5.19	1.88	0.01	7.08	120.54	6.51
4	4.16	1.51	0.01	5.66	98.22	5.10

*Parameters reported are estimated only for this class.
^ Yield expessed in tons.

The profit maximizing levels of fertilizer inputs are computed for the four agricultural capability classes and reported in Table 3-3. The profit computations uses the average price received by farm per bushel of corn in 2006, which is \$3.05, as the corn price (P_c) in the analysis (ERS Feed Grains Database, 2006). The price of nitrogen fertilizer (P_f) is \$0.79 per Kg N- this is corresponding to a nitrogen cost and corn price ratio of 0.12 for pounds of nitrogen and bushels of corn. The cost price ratios usually range from 0.04 to 0.2 and 0.12 is the average cost price ratio (Fox and Piekielek, 1983).

0.12 is also the ratio of fertilizer cost to corn cost per bushel of corn for year 2005 (ERS, Commodity Costs and Returns, Accessed August 2, 2007).

The profit maximizing levels of nitrogen fertilizer input is most (156.21 KgN/hectare) for cornfields operating in soils classified as capability class 1. The equilibrium fertilizer input occurs at that level of input where the marginal cost of the input equals the marginal revenue generated by corn produced by the input usage. The equilibrium fertilizer level decreases as one goes from capability class 2 to 4, in accordance with the decrease in corn yield. Farmers rarely know what the economically optimal amount of nitrogen application ought to be for their fields because they lack the knowledge of corn yield response to nitrogen for their soil, and tend to over apply the fertilizers. As Table 3-3 illustrates, it makes economic sense to lower nitrogen fertilizer application as the agricultural productivity of the soil falls.

3.7.5 Nitrogen Loading and Transport

Ribaudo and Shortle (2001) provide an excellent overview of the suite of models that have been developed for examining relationships between farm practices and loads. On account of the complexity involved in using a spatially referenced watershed based model for nitrogen loading, a simple model that captures the essential features of the more sophisticated model is used in this analysis to model nitrogen load.

Nitrogen fertilizer losses occur through volatilization, uptake in plants, and retention in the soils. Approximately 39% of fertilizers applied are generally lost through volatilization in a watershed (Valiela et al. 1997). This implies that about 61% of fertilizers applied is available for absorption in the soil and uptake in plants. The intercept term, β_{k0} , in the corn yield response to nitrogen function in (3.18) represents the amount of the corn yield that comes strictly from the nitrogen contained in the soil-it is the corn yield that results when the amount of nitrogen fertilizer applied to the soil is zero. Plant uptake of the nitrogen fertilizers is given by the second part of Equation (3.21), $\beta_{k1}(1-e^{-\beta_{k2}x_i})$ *C, where C is the constant that converts corn yield weight in pounds per bushel into the equivalent nitrogen weight in pounds. As per USDA calculations, a bushel of corn that weighs 56 pounds is has .80 pounds of nitrogen in it (USDA NRCS, 2004). If x denote the amount of fertilizer that is applied to the soil, then the balance nitrogen amount entering the soil that is not lost to volatization or is absorbed by the plants, is then equal to $[0.61x_i - \beta_{k1}(1-e^{-\beta_{k2}x_i}) * C]$. The soils vary in the amount of nitrogen that is retained in the soil. Let γ_k denote the soil retentivity coefficient of nitrogen fertilizer in capability k class of soil. Most retention occurs in soils of capability class 1. The runoff (Edge of Field load) for field j in corn production area i (r_{ij}) is given by Equation (3.22).

(3.22) $$r_{ij} = (1-\gamma_k)[0.61x_{ij} - \beta_{k1}(1-e^{-\beta_{k2}x_{ij}}) * C]$$

The loading from each corn production area i (l_i) is the sum of the edge of field load from all farms within the shed i.e. $l_i = \sum_{j}^{n_i} r_{ij}$.

Nitrogen is also dissipitated during transport in the river and is accounted by the attenuation coefficient θ_i for corn producing area i. The attenuation coefficient accounts for the amount of nitrogen loading l_i from the production areas that is removed during pollution transport to the mouth of the river. It is inversely proportional to the distance of the shed from the mouth of the river i.e. the longer the distance traveled by the nitrogen in water, greater is the decay in the nitrogen. The target is to reduce the pollution load L by α % i.e. achieve T such that $T = (1-\alpha)L$. α is set at 25% for the analysis.

3.7.6 Calibration of the Soil Retentivity Coefficients

The average (non adjusted or non dissipated) annual nitrogen loading (per hectare) for the four capability classes obtained from the CRW data is reported in Table 3-3. Using Equation (3.20), the soil retentivity coefficients are calibrated so that it matches the average annual loads obtained from the CRW data for each capability class (Column 2 in Table 3-3). Soils of capability class 1 are found to have the highest retention of nitrogen and consequently give rise to lower edge of stream loads. Capability class 4 soils retain the least amount of nitrogen.

Table 3-4. Capability class based annual nitrogen loading and soil retentivity coefficients

Agricultural Capability Class (k)	Average annual nitrogen loading (KgN)	Soil retentivity coefficient
1	18.74	0.71
2	23.46	0.63
3	20.32	0.62
4	19.83	0.57

3.7.7 Data Simulation

The data for nitrogen fertilizer application rate (x_{ij}), corresponding yield (Y_{ij}), and edge of field load (r_{ij}) is simulated for the 1288 cornfields in the CRW. Each cornfield in the CRW is at a unique location in the CRW, and the location can be captured by the latitude and longitude of that location. The value of the three variables at location s differs from the value of the three variables at other locations within the CRW. In simulating the data, both non-spatial and spatial errors are used to add the maximum possible variation in the population data. The non-spatial errors capture the randomness in the variables that are on account of differences in cultivators' corn variety choices, managerial techniques, knowledge etc. The spatial errors capture the variances in the data across space that results from spatial dependence. The spatial errors are included because the variables under investigation tend to be spatially correlated, and accounting for correlated errors improves precision of the estimates. Equations (3.23) provide the set of relationships that are used to simulate the data for fertilizer application, resulting corn yield, and runoffs for the cornfields.

(3.23a) $$\hat{x}_{ij}(s) = \hat{X} + \varepsilon_x + \varepsilon_x(s)$$

(3.23b) $$Y_{ij}(s\ \ ) = \beta_{ko} + \beta_{k1}(1 - e^{-\beta_{k2}\hat{x}_{ij}}) + \varepsilon_y + \varepsilon_y(s\ \ )$$

(3.23c) $$r_{ij}(s) = [0.61\hat{x}_{ij} - \beta_{k1}(1 - e^{-\beta_{k2}\hat{x}_{ij}}) * c + \varepsilon_r + \varepsilon_r(s)$$

The first equation (3.23a) shows that the fertilizer application at location s is simulated as a variation (captured as errors $\varepsilon_x + \varepsilon_x(s)$) around the mean fertilizer application amount ($\hat{X}$). The analysis uses the Pennsylvania State University's Agricultural Analytical Services Lab 2005-06 recommendation of 134 lbs of nitrogen per acre (150KgN/hectare) for Lancaster County, PA as the mean fertilizer amount ($\hat{X}$) applied in the CRW. The non-spatial errors ε_x were randomly drawn from normal distribution with mean zero and standard deviation of 20.

The model used for generating the spatial errors assumes that the variance of the difference in fertilizer application levels at location s and t equals

(3.24) $E[(x_s - x_t)^2] = 2(\mu^2 + \sigma^2 + E[x_s x_t])$

A *variogram* expresses the variance as a function of the distance between the two locations. If the distance between the two sites is beyond a certain critical level (called range), then it is assumed that the covariance between the two sites is zero. In that case $E[x_s x_t] = \mu^2$, and the variogram equals the overall fertilization application variability in the watershed, σ^2. In other words, when the any two locations are so far apart that application rates are uncorrelated or spatially independent, the variance between the two locations equal σ^2. In this case, the fertilization application rate at one location provides no additional information about the fertilization application rate at the other location. For locations closer to one another, the variance of the difference in fertilizer application rates decrease and application rates become more correlated. That is, the locations are close enough for the fertilizer application rate at one location to provide additional information about the fertilizer application rate at another location. The fertilizer application levels between any two locations is assumed to follow a Whittel Matern variogram, which is given by

(3.25) $2\gamma(d) = C_0 + C_1(1 - \frac{(d./2a)^{\nu}}{2\Gamma(\nu)} K_{\nu}(d/a)$

where

$2\gamma(d\;)$ = Variance in the difference between fertilizer application rates at the two locations which are d distance apart

d = distance between the locations

a = range

C_0 = nugget effect,or the local random component of the variation in fertilizer application rates that cannot be explained spatially

C_1 = fertilizer application rates that can be explained spatially= σ^2

$K_v(.)$ = Modified Bessel Function of the second kind with parameter v

v = Parameter that controls the smoothness of the random field i.e. how the variation in difference in fertilizer rates between any two locations change with distance between the two locations .

The Whittle Matern variogram was selected as the variogram model for the smoothness parameter that allows simulation of smooth random spatial fields across the watershed. The 'RandomFields' package provided with the statistical software R is used to simulate the spatial model described above. The spatial simulation produces a set of realizations of the fertilizer application rates for each cornfield in the CRW such that it preserves the mean and the covariance structure that has been specified for fertilizer application rates for the CRW.

Once the data for fertilizer application levels have been simulated for the 1288 cornfields in the CRW, the values are plugged into the estimated corn yield function to generate values of corn yield for the cornfields. Equation (3.23b) shows that corn yield for any cornfield at location has a fixed part (given by $\beta_{ko} + \beta_{k1}(1 - e^{-\beta_{k2}\hat{x}_{ij}})$, where k is the relevant agricultural capability class for the cornfield), and a random part given by non spatial and spatial errors $\varepsilon_y + \varepsilon_y(s\ )$. The non spatial errors were drawn from a normal distribution with mean zero and standard deviation 1.432, which is the standard deviation of corn yield as established by secondary data for Lancaster County, PA (Fox and Piekielek 1983). The spatial errors for corn yield were simulated for a spatial random field for the Whittle Matern covariance structure corresponding to specifications listed in Table 3.5. Equation (3.23c) shows edge of field runoff for each cornfield corresponding to the simulated nitrogen fertilizer application rate and yield for that cornfield. The non-spatial errors ε_r are random draws from N(0, $\sigma^2(k)$), where $\sigma^2(k)$ is the standard deviation of runoffs for capability class k as established by the CRW loading data. The simulated field for runoffs are assumed to have Whittle Matern covariance structure similar to fertilizer applications, with specifications listed in Table 3.5. The range specified for the simulated fields is least for fertilizer applications levels, and is the most for runoffs.

Tables 3–5: Specifications for the errors structures

Variable	Non Spatial Errors	Spatial Errors* Range(in kilometers)
Fertilizer Application	N(0, 20)	0.08
Corn Yield	N(0,1.432)	0.16
Edge of Field Runoff	N(0, 7.11) for k=1 N(0, 6.59) for k=2 N(0, 7.37) for k=3 N(0, 8.85) for k=4	0.48

The simulated Gaussian spatial random fields assumes a Whittle Matern Covariance Structure with zero mean, variance1, nugget=0, scale1, and the range listed in the table.

3.8 Sampling Strategies

The two sampling strategies considered in this analysis are (1) environmental sampling and (2) integrated sampling of the environment and the economy. The former results in the gain of perfect information about the attenuation coefficients for the m corn production areas. The latter yields imperfect information on corn yield and runoff parameters for the m production areas. Imperfect information on the attenuation coefficients makes it possible to design non-uniform production area specific standards for corn fertilizers that allocate total nitrogen loading in the CRW among the production areas such that the loading per unit area is equal for all corn production areas. Environmental sampling therefore helps to identify the pollution types of the cornfields and enables standards that penalize fertilizer use to the extent that it contributes to nitrogen pollution.

To determine the attenuation factors, data is required on the total nitrogen runoff from each corn production area and the distance traveled by the nitrogen in the streams to the mouth of the watershed. In real life this would mean sampling for the nitrogen load, stream velocity and decay rate of nitrogen in the streams in each corn production area. For the analysis, the attenuation coefficient factors are known from the data on simulated nitrogen load and distance traveled in the stream. The sampling exercise is not actually performed but is assumed. The sampling exercise assumes full sampling of all 43-corn production areas and all 43 attenuation factors are known at the end of the information collection exercise.

For obtaining imperfect information on the parameters of corn yield and runoffs (i.e. information structure I=3), the essay uses a two stage sampling methodology. Under two stage sampling, a popular sampling method used by the National Agricultural Statistical Services (NASS), sampling occurs in two stages. In sampling terminology, the area frame of sampling refers to the area that is to be collectively sampled-it is broken down into smaller parcels or units of land for the purpose of later sampling of the parcels or units. In the first stage of sampling, the parcels or the unit of land are randomly selected for sampling-the units selected in the first stage are referred to as the primary sampling units. In the second stage of sampling, entities within each parcel or unit are selected for further sampling.

The CRW with the 43 corn production areas make up the area frame for sampling. In the first stage, a predetermined number of production areas (say p% of the 43 sheds) are randomly selected from the population of corn production areas. In the second stage, a selected number of fields (say q %) from the population of cornfields in each shed is randomly selected and sampled. The production areas are the primary units of sampling while the fields are the secondary units. The total number of sample points is the sum of all cornfields sampled. In the baseline run, a total of 5, 14, 4, and 3 corn production area are selected respectively for each of the four agricultural capability class k=1, 2, 3, and 4. This is done to ensure an adequate representation of all capability classes in the selected samples, particularly as there are not many production areas hailing from agricultural capability classes 3 and 4 in the analysis. This implies that a total of 26 primary units are sampled i.e. g = 26. About 50 % (q = 0.5) of the cornfields are sampled in each production area. The maximum number of fields sampled in any shed is restricted to 30.

In each sample draw, data is collected on the nitrogen application rates and yield and edge of field load, for the fields selected in the sample. A total of 100 sample draws are replicated and the average value of the estimated parameters of the yield and load function obtained from the 100 samples are taken as the expected value of the parameters that can be obtained from any one sample draw

3.9 Results

The environmental target used in the analysis reduces the total pollution loading L in the Conestoga watershed by 25%. The total annual nitrogen loading in the Conestoga River amounts to 335 thousand of kilograms of nitrogen. At 25% reduction, the targeted nitrogen load (T) is approximately 251 thousand of Kg N. The baseline unrestricted profit, the profit under no regulation, for the population of 1288 fields at specified prices of corn and fertilizer calibrates to $ 24.7 millions.

Table 3-6 reports the aggregate profits from corn production corresponding to the three vector of standards that arises from the three information structures- uniform standards (s_1 |I=1) designed in the absence of any information on the productivity or pollution type of the fields, heterogeneous standards ($\mathbf{s_2}$ |I=2) designed using environmental (pollution type) information, and more comprehensive standards ($\mathbf{s_3}$ **|** I=3) designed using integrated information on the environment (pollution types of the sheds) and the economy (productivity type of field in each shed). The restricted profits increase as the information structure expands from I=1 to I=3. The reduction in profits from the baseline profits is the least for I_3 when the standards are designed using information on both the economy and the environment.

Table 3-6. Value of information for alternative information structures

Information Structures	Aggregate Profit (million $)	Reduction in Profits[1] (million $)	Expected Value of Information (million $)[2]
I_1-No information	23.67	1.03	-
I_2-Environmental information only	23.92	0.78	8.6
I_3- Integrated environmental and economic information	24.14	0.56	16.1

[1] Reduction in profits is calculated from baseline profits (24.7 million dollars). It is the cost of enforcing the standards.

[2] Expected value of information, (EVOI), is computed as the sum of discounted savings in profit reduction (relative to the no information case).

Table 3-6 also reports the Expected Value of Information for the three information structures. The expected value of information is respectively $8.6 and $ 16.1 for information structures 1 and 2 under the sampling specifications. The EVOI of integrated information of the economy and the environment is the highest, almost the double of that of environmental information only.

3.10 Sensitivity of EVOI to Alternative Sampling Strategies

The Expected Value of Information of an information structure depends on the sampling strategy (design and intensity of sampling) that is used to collect that information. Intuitively, it is expected that the more intensively sampling occur in any sampling strategy, the more would be the Expected Value of Information corresponding to that strategy. This is because the greater quantity of data generated from intensive sampling would yield more precision in the estimation of the corn yield and runoff parameters. In testing for the value of information in integrated sampling designs of the environment and the economy, it needs to be seen whether the expected value of information is sensitive to the sampling design i.e. choice of the number of primary units (sheds) and number of secondary units (cornfields) within the selected primary units that are sampled.

Table 3-7 reports the Expected Value of Information corresponding to four different sampling designs denoted by A, B, C, and D. A refers to the design of randomly sampling (1) 5, 14, 4, and 3 of the total number of sheds of k=1, 2, 3 and 4, and (2) 50% of the cornfields in each of the selected shed-this is the sampling strategy considered in the previous section, the EVOI corresponding to which was reported as $16.1 million. B hold the number of corn production areas sampled the same as in A but samples 25 % of the corn fields in each of the selected production area-this results in fewer cornfields being sampled under design B compared to design A. In C, the number of primary units sampled changes-only 4, 7, 3, and 2 of the total number of corn production areas corresponding to k=1, 2, 3,and 4 are sampled with 50% of the cornfield within each production area being sampled. D is same as C excepting that only 25 % of the fields is being sampled in each randomly selected corn production area. The reason for exploring the EVOI of integrated sampling of the environment and the economy under these four sampling designs is to investigate the relative importance of the primary units and secondary units in determining the EVOI measure.

Table 3-7: Expected value of information under alternate sampling designs

Sampling Design	Expected Value of Information
(A) $(g_1 = 5, g_2 = 14, g_3 = 4, g_4 = 3; m_j = 0.5*M_j)$	16.1
(B) $(g_1 = 5, g_2 = 14, g_3 = 4, g_4 = 3; m_j = 0.25*M_j)$	14.3
(C) $(g_1 = 4, g_2 = 7, g_3 = 3, g_4 = 2; m_j = 0.5*M_j)$	15.8
(D) $(g_1 = 4, g_2 = 7, g_3 = 3, g_4 = 2; m_j = 0.25*M_j)$	15.7

1. All figures in million dollars
2. m_j=number of cornfields sampled in each selected shed j; M_j= maximum number of cornfields in the j^{th} shed.
3. g_i, i=1,2,3,4 is the number of sheds selected for sampling in the i^{th} capability class.

True to expectation, the Expected Value of Information is the highest for sampling strategy A-the maximum number of fields is sampled under this strategy. The Expected Value of Information is much reduced under sampling strategy B where a fewer number of cornfields are being sampled in each selected shed. Surprisingly, strategy C and D perform well in terms of EVOI. Although the total number of sheds and fields sampled under the strategies C and D are much lower than the number sampled under strategy A, the EVOI under C and D is fairly comparable to the EVOI under A. The EVOI differs very little between strategies C and D, demonstrating that under the same selection of primary units, the intensity of sampling of the secondary units does not affect the EVOI. The EVOI is robust across the different sampling strategies, although selection of primary sampling units appears to affect EVOI more. The sensitivity analysis suggests that careful consideration must be given to the sampling strategy as strategies with greater emphasis on sampling primary units yields higher value of information.

3.11 Conclusion

There appears to be Value of Information (VOI) in integrated sampling of the economy and the environment. Integrated information procurement not only enables more efficient pollution control choices that minimizes the cost of pollution control for society but also provides an equity basis to pollution load allocations. It is indeterminate in the analysis the extent to which the value of information is sensitive to the costs of information procurement. Inclusion of assessments of the costs can make the analysis of value of information of integrated sampling approach more concrete.

The results have implication for the way resources are expended in collection of data. Non-integrated collection of data on multi aspects cannot be fruitfully used if their spatial scales of the data cannot be matched. NASS can collect as much of county level economic data but it would be of no use if that data cannot be used to inform pollution control policies in watershed quality management. The emphasis is on developing a uniform basic sampling frame for sampling many different types of environmental data. The information obtained from multiple sources can be used effectively only if they can be integrated successfully into decision-making.

Further explorations of the VOI analysis can investigate whether the results are robust to alternative specifications of the simulated population and the choice of pollution control instruments like tax or tradable permits. Robust results strengthen the case for immediate effort investment in integrated sampling of the environment and the economy. Future efforts can also research optimal sampling strategies for information acquisition that exploit spatial interaction between sample points and use Bayesian updating for refining the choice of sampling points.

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VITA

EDUCATION

Master of Arts (December 2000): Jadavpur University, Calcutta, India
Major: Economics
Fields: Resource and Environmental Economics, Econometrics, Quantitative and Optimization Techniques

Bachelor of Arts: (December 1998) Jadavpur University, Calcutta, India
Major: Economics (Honors)

SELECTED PROFESSIONAL PRESENTATIONS

- *Koel Ghosh, James S. Shortle, and Carl Hershner.* Socially Optimal Strategies for Ecological restoration under Climate Change. *American Agricultural Economic Association (AAEA). Denver, Colorado, August 2004.*
- *Koel Ghosh, James S. Shortle, and Carl Hershner.* Socially Optimal Strategies for Ecological restoration under Climate Change. *Canadian Agricultural Economic Society (CAES) -Northeastern Agricultural and Resource Economics Association (NAREA). Halifax, Nova Scotia, June 2004.*
- *Koel Ghosh, James S. Shortle, and Carl Hershner.* Optimal Investment in Ecological Conservation and Restoration Projects under Climate Change: A Spatial Intertemporal Analysis. *Open Meeting Human Dimensions of Global Environmental Change organized by the International Scientific Planning Committee. Montreal, October 2003.*
- *Koel Ghosh and Elizabeth P. Marshall.* Modeling Strategic Interactions in Land-Use Decision Models. *Selected Paper, Annual meeting of American Agricultural Economics Association (AAEA). Long Beach, California, July 2002.*

HONORS & AWARDS

- *The Honor Society of Agriculture, Gamma Sigma Delta,2004*
- *Third Prize, Social Science Category, Graduate Research Exhibition, Penn State University 2004*
- *College of Agricultural Science Graduate Student Travel Award, Pennsylvania State University, 2002.*

RESEARCH EXPERIENCE

The Food Industry Center, University of Minnesota — Nov. 2004-present
Research Fellow

Department of Agricultural Economics and Rural Sociology — May 2001 – Oct. 2004
The Pennsylvania State University, University Park, PA
Research Assistant

Department of Environmental and Natural Resource Economics — Sep. 2000 – Apr. 2001
University of Rhode Island, RI
Research Assistant

TEACHING EXPERIENCE

The Pennsylvania State University — *Fall 2002*
Instructor, AG EC 597 E “Applied Microeconomics Seminar”