Three Essays on Watershed Modeling, Value of Water Quality and Optimization of Conservation Management

DISSERTATION

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By

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ABSTRACT

Conservation management practices are considered one of the best answers to escalating water quality deterioration by nonpoint source pollution. Integrated watershed economic model (IWEM) offers a multidisciplinary framework by addressing both the biophysical and the economic (cost and benefit) aspects of water quality improvement. An IWEM can be conceptualized as three sub-models: a watershed model, an economic model, and an optimization tool to integrate the watershed and economic models together. The present study is an attempt in this direction, by translating the three sub-models of IWEM into three essays of the dissertation. The Upper Big Walnut Creek (UBWC) watershed in central Ohio was selected for applying the IWEM framework.

The modeling of the UBWC watershed was performed in the first essay. For this study the Soil and Water Assessment Tool (SWAT) was used to predict the nutrient export associated with land management practices. SWAT was selected because of its proven worthiness as a tool for understanding the watershed-scale management impact on nutrient loading from agriculture. A new integrated calibration procedure was introduced for the calibration and validation of the UBWC watershed model, where components of the water balance were evaluated along with crop yield and nitrogen balance. The predicted flow for daily, monthly and annual time scales were not statistically different from the measured values. Additionally, the timing of the predicted runoff events also followed the measured timing, and met the efficiency criteria of calibration and validation. The evaporation and transpiration and leaf area index of corn, soybean and wheat over the

growing period were also accurately predicted. Also, the predicted crop yield was statistically not different from the reported values. Nitrate fluxes, calibrated using the field measured values at the two paired sub-watersheds, predicted nitrate loading was statistically not different from the measured values. Additionally, sensitivity and uncertainty of the model for flow and nitrate load were analyzed in detail. The uncertainty analysis showed that the model predicted flow and nitrate load was with the lowest uncertainty. Following calibration and validation of SWAT for UBWC, the SWAT model is qualified for predicting the impact of different management scenarios on nutrient loading.

Recreational value of water quality improvement is one of the major shares of economic benefits derived from water quality enhancement. Thus, recreational demand analysis was applied to UBWC watershed, which was described in the second essay. A survey method was used, in which 1400 registered anglers and licensed boaters in 5 surrounding counties of the watershed were selected for the study. The survey gathered a wide range of information from the visitors, which included the number of times they had visited the different zones of UBWC watershed during 2008, demographic variables, and details about trip activities. As the goal of this study was to measure the recreational value of water quality from the current level of water quality impairments to the desired level as per the EPA standards, two scenario-based questions were also included in the survey. The two scenarios were, (i) how many trips they would have taken in 2008, if they had information about water quality impairments in the watershed, and (ii) a hypothetical water quality improvement scenario was provided and then asked the respondents to state how many additional trips they would have taken to each zone under improved water quality conditions. A combined revealed and stated preference method with baseline dependence and unobserved heterogeneity modeling was attempted in this study. The results showed that the new information about water impairments in the watershed would shift the demand curve downwards, and that about water quality improvement would shift the demand curve upwards. The baseline average number of trips was 2.35, which was reduced to 1.72 with more information about pollution level in the watershed. However, water quality improvement would increase the number of trips to 2.78. The average annual consumer surplus was $52.23, $28.09 and $91.11 for baseline, trip with more pollution information and trip with improved water quality conditions, respectively. The estimated annual aggregated benefit for baseline visit was $2.03 million. But, if the current information about water quality impairments were available to the visitor when they made their trip plans, aggregate surplus would have reduced to $1.09 million. However, water quality improvement would make significant increase in benefit to $3.53 million.

In the third essay, an integration tool was used for integrating the watershed and economic models presented in the above two essays. A dynamic programming-based economic optimization approach was used in this study. The method could capture the nutrient movements in agro-ecosystems, starting from nutrient application, intake by plants and transport from the field to downstream water reservoir with possible nutrient assimilation in-between. This approach is also able to integrate farmer's profit function by internalizing the social cost associated with the pollution. The watershed modeling results from essay 1 and the benefit estimates from essay 2 were used to specify the objective and transition functions of the dynamic program. The social cost of the pollution is

parameterized with benefit estimates of water quality improvement. Model is developed for the entire watershed by considering it as a single homogeneous one hectare unit. The watershed model was used to simulate the baseline, and crop rotation and conservation technology-specific production functions. Two sets of conservation technologies were developed for the watershed. One with cover cropping, conservation tillage and vegetative buffer stripes and the other with split nitrogen fertilizer application, cover cropping, conservation tillage and vegetative buffer stripes. The analysis revealed that under no restriction on pollution loading, farmers would apply a maximum of 170.51kg/ha of N and the value function would be $7950 under C-S-W rotation. The fertilizer application rate was reduced to 103 kg/ha when cost of pollution was internalized in profit. Within the crop-technology combinations, split-N application, conservation tillage, cover crop showed the lowest pollution load to the reservoir along with higher value function. However, the realized profit and crop yield were less compared to unrestricted production conditions. Thus, it could be concluded that the present level of private profit and yield levels are not realized by adopting both the technology sets considered in this study.

Dedicated to my family

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FIELDS OF STUDY

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CHAPTER 1

INTRODUCTION

In the United States, nutrient pollution is the leading cause of water quality issues in lakes and estuaries (USEPA, 1998). Non-point source pollution (NPS) has been identified as a significant contributor to water quality degradation and it remains unregulated (Goolsby et al., 1999; Rabalais et al., 2002). It is alleged that agricultural activities are the leading source of NPS, causing impairment in lakes, ponds, reservoirs, rivers, and streams (USEPA, 2002). This is not surprising because, agricultural crops are the single vegetation groups receiving the highest external chemical inputs for production. Clearing of natural vegetation for agriculture purposes, and leveling of natural channels coupled with tillage and other cultural practices increase erosion and off-farm migration of nutrients (Lovell and Sullivan, 2006). NSP adversely affects designed use of water, such as drinking, recreational, agricultural, and industrial purposes (USEPA, 2002). Furthermore, NPS considerably diminishes the aesthetic value of water resources and more seriously, destroys the aquatic and land biodiversity (Carpenter et al., 1998). Therefore, society expects the agricultural sector to follow and adopt proper natural resource conservation practices for reducing NPS load from agriculture, along with higher productivity aspiration.

In response to the escalating water quality threat by NPS, the United States Environmental Protection Agency (USEPA) mandates individual states to implement the Total Maximum Daily Load (TMDL), the maximum allowable load of a contaminant that a water-body can receive while still meeting its water quality standard (USEPA, 2002). Current public and private costs associated with this effort are estimated to be $1.035 billion for the development of TMDL plans, $255 million for additional monitoring to support TMDLs, and $13.5 to $64.5 billion for the implementation of TMDL plans over the next fifteen years (Tegtmeier and Duffy, 2004). The state of Ohio is also actively involved in TDML and other NPS reduction programs. The Upper Big Walnut Creek watershed (UBWC) in central Ohio was identified as one of the impaired watersheds that do not meet state water quality standards due to NPS from agriculture (Ohio EPA, 2005). The UBWC encompasses perennial and intermittent streams that drain into Hoover Reservoir, and serves as a primary source of drinking water supply and a favorite local recreational site for residents in the neighboring communities.

In this context, availability of a method for an ex-ante evaluation of conservation management, and an assessment of their efficacy in controlling nutrient load in a cost effective way would help transfer TMDL policies to real world actions. However, development of such a method for controlling NPS is challenging because of many reasons including the dynamic and diffuse nature of NPS from agriculture field (Naevdal, 2001; Carpenter et al., 1999 and Ribaudo et al., 1999), uncertainty about the nutrient load, the spatial and temporal variability in nutrient transport, and the complexity in defining accurate relationship between human activities and the nutrient load.

Additionally, one to one matching between nutrient loads and environmental damage is relatively difficult in a complex biophysical realm (Elofsson, 2003), and complications in measuring economic damages caused by pollution (Ribaudo et al., 1999) would make NPS regulation a really daunting policy task.

In order to evolve a policy analysis framework for addressing the issues identified above, redefining the NPS issues in a multidisciplinary background with clear understanding of both biophysical processes and socio-economic context of the watershed, along with a proper interaction between the two is essential. Along these lines, an integrated watershed economic modeling (IWEM) by linking the biophysical process component with the economic behavior component would be useful to draw the blueprints of policy guidelines. Such an IWEM would have three components (Fig.1.1), a biophysical process model component, an economic behavior component and a tool to integrate both the biophysical and economic components. The biophysical component uses spatial scale climate, soil and terrain properties along with site specific management variables to predict an array of possible site specific best management practices (BMP). Thus, the biophysical process component of the IWEM could preserve the heterogeneity across the watershed, and simulate the watershed behavior consistent with established scientific understanding (Antle and Capalbo, 2001). The economic behavior component would be able to portray the economic rationale of the technologies and crop-mix options along with explicit description of costs and benefits associated with nutrient loading reductions of various management options. The integration tool decides the level of aggregation of the heterogeneity in biophysical and economic components, which vary from aggregating at watershed scale to very detailed description of biophysical and economic heterogeneity in the watershed. Thus, the IWEM can be effectively used to represent the agricultural and environmental ‘*cause-effect*’ relationship of spatially differentiated land management strategies in watershed to manage downstream water quality.

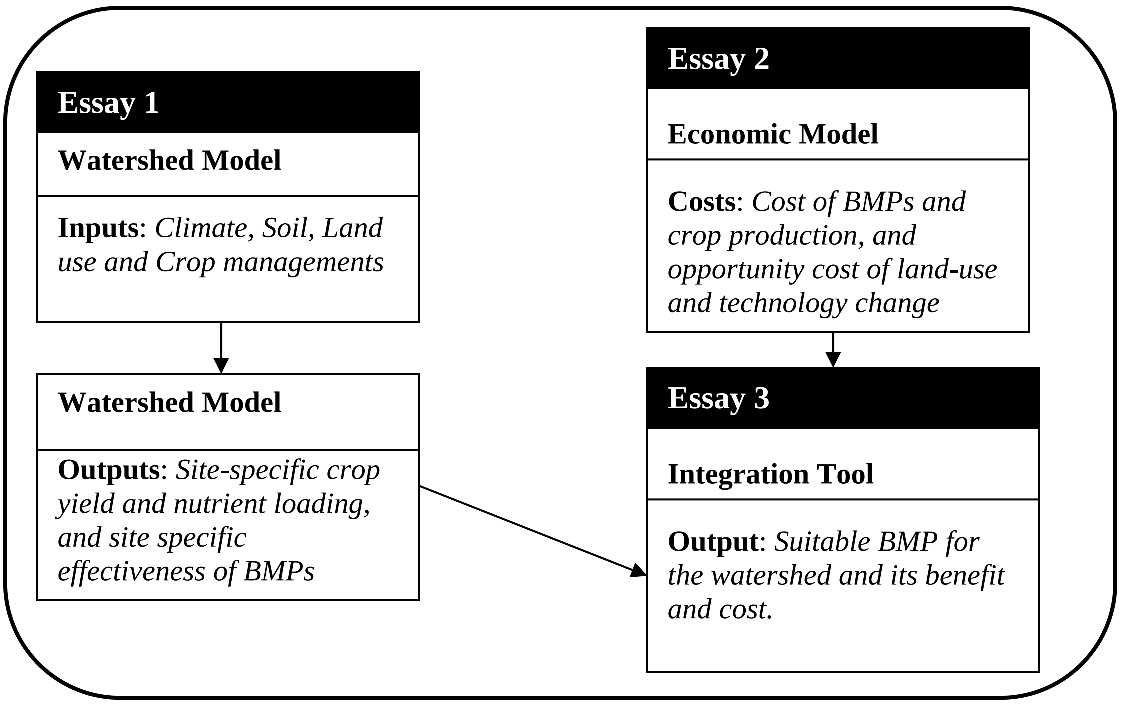

Fig.1.1. Components of integrated watershed economic model.

Dissertation outline

In this research, the above mentioned three components of the IWEM are translated into three essays. The first essay is about biophysical modeling of UBWC watershed for water quality applications. The second essay is on the application of non-market valuation for estimating the recreational demand associated with water quality improvement. The third essay presents integration of the benefit and cost of BMPs evaluated by biophysical model to arrive an optimal targeting of BMPs for the UBWC watershed.

Essay 1: Calibration, validation and uncertainty analysis of SWAT model in a watershed for water quality studies

The success of any on-farm and off-farm BMP intervention to reduce NPS load from agriculture depends on provision of methodologies that can be used to evaluate the site-specific effectiveness of the BMPs. A computer-based watershed-scale biophysical process model would be a useful tool in BMP evaluation mainly for two reasons: (i) biophysical process simulation model could preserve the existing heterogeneity in the watershed, and (ii) an ex-ante evaluation of probable BMPs are possible in computer based modeling framework.

The UBWC is one of the 14 watersheds studied intensively by United States Department of Agriculture (USDA) for evaluating the effectiveness of BMPs for reducing nutrient load from agriculture. The information generated by USDA through field experiments is a valuable data source for developing the watershed model for UBWC. Thus, the present study was designed to develop a watershed-scale model specific to UBWC using the Soil and Water Analysis Tool (SWAT) for scientific evaluation of BMP technologies with the help of the extensive dataset generated by USDA.

Essay 2: Recreational value of water quality improvement in the Upper Big Walnut Creek Watershed, OH.

A policy analysis always has to account for the probable benefits and cost of a prescribed strategy for an environmental improvement. When considering land and landscape management options for addressing the NPS from agricultural practices, policy makers may wish to have estimates of the economic value of the benefits generated by the proposed policy. An improvement in water quality generally provides two broad classes of economic benefits: withdrawal benefits and in-stream benefits (Feenberg and Mills, 1980). Withdrawal benefits include direct consumption of water (household use and other) and as an input in other production processes (industry and agriculture). In-stream benefits are use value of water quality (swimming, boating, sport- fishing and others) and non-use value of water quality (existence value, future option value and bequest value). As most of the services related to water quality improvement will never reach the market for price formation, non-market economic evaluation methodologies would be appropriate to arrive the true economic value. A base dependent and unobserved heterogeneity modeling was applied to combine the revealed and stated preference data set.

In UBWC, recreational value of water quality improvements has not been quantified yet. Therefore the focus of this study was to estimate the potential recreational value (both boating and fishing) of water quality improvements in UBWC. It is hypothesized that with an improvement in NPS reduction by implementing the BMP in agriculture, the associated use and non-use benefits will also increase.

Essay 3: Integrated watershed economic model for non-point source pollution management in Upper Big Walnut Creek Watershed, OH.

The basic premises where integration of watershed scale biophysical model and economics operates watershed services includes marketed and non-marked economic functions, thus have economic value. In addition, economic rationale of agricultural technology, crop-mix selection and associated negative externality would affect the quantity and quality of watershed services provided to the society. If a framework could represent both biophysical and economic systems with sufficient interaction between them, such a framework would be the most useful for deriving the benefit and cost associated with possible BMP for reducing the NPS from agriculture. This essay describes an optimization-based integration of watershed scale biophysical process model with economic model to derive optimal agricultural management strategies for NPS reduction in UBWC, OH.

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CHAPTER 2

ESSAY 1

CALIBRATION, VALIDATION AND UNCERTAINTY ANALYSIS OF SWAT MODEL IN A WATERSHED FOR WATER QUALITY STUDIES

2.1 Introduction

Non point source (NPS) pollution is the leading cause of water quality impairments in U.S (USEPA, 1998). Implementation of the 1972 Clean Water Act has substantially reduced point source pollution. However, the off-target migration of nutrients and pesticides applied on cropland continues to pose significant risks to terrestrial and aquatic ecosystems in the United States. Recent research identified nutrient flux from agricultural lands in the Midwestern United States as causing aquatic ecosystem degradation along the Mississippi river basin and hypoxia in the Gulf of Mexico (Goolsby et al., 1999; Rabalais et al., 2002; USEPA-SAB, 2007).

To address water quality concerns, the United States Environmental Protection Agency (USEPA) mandated individual states to implement Total Maximum Daily Load programs (TMDL), (USEPA, 2002). In addition, federal funding for conservation programs has increased considerably, expanding the use of conservation management (Mausbach and Dedrick, 2004), considered to be the best method for minimizing agricultural NPS pollution and sustaining production (Ice, 2004). The State of Ohio is actively involved in the TDML process and other NPS reduction programs. The Upper Big Walnut Creek watershed (UBWC) in central Ohio was identified in 1998, 2000, 2003 and 2004 as a priority impaired watershed in the Section 303(d) list (CWA, 1972) of waterbodies that are not meeting state water quality standards. The UBWC encompasses 492 km^2 in central Ohio and contains 467 km of perennial and intermittent streams that drain into Hoover Reservoir, which serves as a primary source of drinking water supply and a favorite local recreational site for residents of Columbus and surrounding communities (Ohio EPA, 2005). The majority of headwater streams in the watershed are impaired by nutrient enrichment, stemming from current agricultural management practices (Ohio EPA, 2005).

The success of any pollution reduction program depends on availability of suitable methods and tools to evaluate the effectiveness of the proposed programs in improving water quality. Two approaches can be used for TMDL evaluation: (i) use of field-based experiment results to quantify and evaluate the impact of conservation practices, and (ii) use of biophysical process models to simulate and evaluate different conservation practices (Shirmohammadi et al., 2006). However, the extent of spatial and temporal variability in the biophysical components of an ecosystem requires multiple field measurement locations and frequent sampling. Furthermore, an ex-ante evaluation of conservation practices is not economically feasible solely using the field measurement approach. In contrast, computer-based watershed scale biophysical process models with careful parameterization can address spatial and temporal variability within an ecosystem and also allow prediction of the ex-ante site-specific effectiveness of multiple conservation practices. Thus, biophysical process models provide an essential framework for scientific assessment that helps to understand site-specific efficacy of conservation management. However, even with a very complex model, detailed ecosystem process description is only an abstract representation of natural process. Quantifying the uncertainty is a crucial part of interpreting the model generated results (Stow et al., 2007). Hence, uncertainty analysis is required to provide an indication of the range of probable deviations in the model results (Sohrabi et al., 2003).

For this study the Soil and Water Assessment Tool (SWAT; Arnold et al. 1996) was used to predict water quality changes associated with land management practices. SWAT was selected because of its proven worthiness as a tool for understanding watershed-scale management impact on nutrient loading from agriculture (Santhi et al., 2001; Kirsch et al., 2002; Santhi et al., 2006). Moreover, the comprehensive model structure makes SWAT a broadly applicable tool for predicting water quantity and quality outcomes from alternative land management practices. Additionally, Borah (2004) reviewed several continuous simulation models and single-event watershed models for their usefulness in modeling nutrient export with different land management strategies at a watershed scale and suggested that SWAT was superior to the other evaluated models.

The objectives of this study were to:

1. Calibrate and evaluate SWAT (version 2005) for simulating stream flow, total nitrogen flux and crop yield for the UBWC watershed, and
2. Perform selected parameter uncertainty analysis with the calibrated SWAT model for the UBWC watershed.

2.2 Materials and methods

2.2.1 SWAT 2005 model and ArcSWAT interface

SWAT is a physically based, watershed-scale continuous time simulation model operating on a daily time step (Arnold et al., 1998). SWAT can be used to simulate long-term impacts of climate change, land cover and land use practices and management strategies on water flow, crop/vegetative growth and water quality parameters such as sediment and nutrient load from watersheds (Saleh et al., 2000; Vaché et al., 2002; Chu et al., 2004; Hu et al., 2007). SWAT requires numerous inputs to parameterize its major components: hydrology, weather, erosion, crop growth, nutrients, pesticides, and management activities.

2.2.2 Watershed description

The UBWC watershed is an 11-digit watershed located in central Ohio (40°06’00” latitude and 82°42’00” longitude), a humid and hot summer climatic region of the United States (Fig.2.1). Normal daily temperatures range from an average minimum of -9.6°C in January to a maximum of 33.9°C in July. Normal annual rainfall in the watershed area is approximately 985 mm. Monthly rainfall follows a bimodal distribution with peaks during late spring-early summer and late fall-early winter (King et al., 2008).

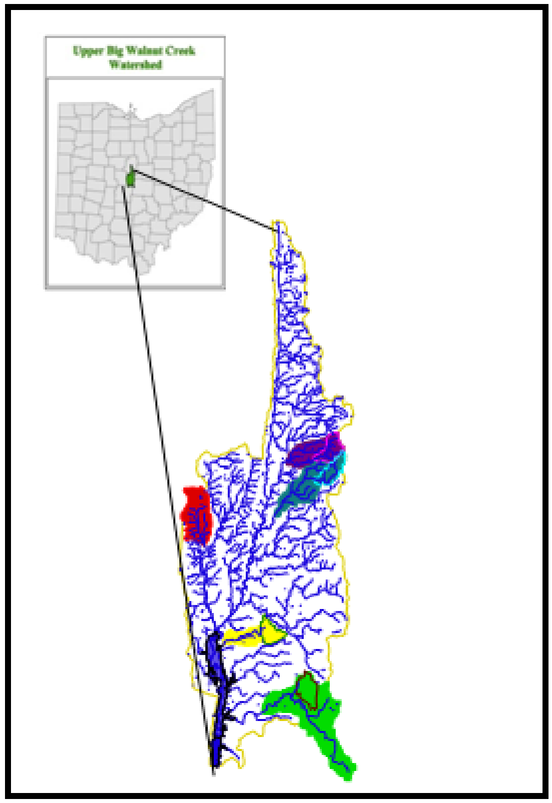

Fig. 2.1 The Upper Big Walnut Creek Watershed, Ohio.

The most prevalent soil associations present in the watershed are the Bennington-Pewamo-Cardington association (60%) and Centerburg-Bennington association (20%), which are nearly level, clayey and poorly drained soils (USDA, 1993). Agriculture is the dominant land-use with corn, soybean and wheat as principal crops (NASS, 2005).

Typical agricultural management includes conservation tillage, fertilization and herbicide application for corn, soybean and wheat.

2.2.3 Watershed and hydrologic response unit delineation

The watershed boundary was delineated with the ArcSWAT interface using a USGS 7.5-minute digital elevation model (DEM) data and a pre-defined digital stream network. The watershed was divided into eight sub-watersheds with a threshold drainage area of 2500 ha. ArcSWAT divides a sub-watershed into smaller discrete hydrological response units (HRU) with homogeneous biophysical properties using slope, soil and land cover maps. Unlike sub-basins, HRUs do not have to be contiguous units, but rather include all parcels of land within the sub-basin with similar properties. So, HRUs can be described as any area within a sub-basin with a unique combination of slope, soil type and land use, receiving specific management practices. The data layers required for defining HRUs were obtained from different sources. The land cover map of UBWC watershed was derived from National Land Cover Data (2001) and slope classes of the watershed were calculated within SWAT using DEM. The medium resolution (1:250,000 scale) soil map, STATSGO was used to characterize soils in the watershed. The multiple HRU option available in SWAT was used to generate HRU's, which more accurately depicts the heterogeneity within a sub-watershed by generating more than one HRU in each of the sub-watersheds. To avoid a large number of generated HRUs, only the land cover, soil and slope classes with comprising more than 5% of sub-watershed area were considered for HRU creation. Initially 176 HRUs were generated, but one of the agricultural HRUs had 3012 ha land area, almost 10% of the agricultural land-use in the watershed. So each of the agricultural HRU were divided into 6 equal parts in order to limit the size of a single agricultural HRU to 3% of the watershed area, which resulted in a total of 376 HRUs. The percentage of area under different land-uses and soil classification before and after HRU delineation was comparable (Table 2.1).

	Before HRU delineation	After HRU delineation
Land cover	% of Watershed area	
Agricultural-Land-Row Crop	48.59	47.56
Forest-Deciduous	24.90	25.75
Hay	13.56	13.72
Residential-Low	6.83	6.76
Water	2.51	2.71
Residential-Medium	1.42	1.29
Other	2.19	2.21
Soil type	% of Watershed area	
Bennington-Pewamo-Cardington	57.67	56.66
Centerburg-Bennington	19.65	19.48
Cardington-Alexandria	14.76	15.95
Amanda-Centerburg	3.54	3.46
Bennington-Centerburg	2.41	2.32

Table 2.1 Land cover and soil types classified by SWAT for the study area.

Climatic inputs of UBWC watershed during the study period (1990-2005) were collected from different sources. National Climatic Data Center's weather stations at Westerville and Centerburg provided daily precipitation. Other climatic inputs, such as daily maximum and minimum temperatures, solar radiation, wind speed and relative humidity were obtained from Ohio Agricultural Research and Development Center's weather station at Delaware, Ohio. Preprocessing of the SWAT model input was performed using the ArcSWAT interface [Winchell et al., 2007] within ESRI ArcGIS 9.2 (ESRI, Redlands, CA).

2.2.4 Agricultural management

SWAT requires detailed information regarding land use management practices such as crop type, planting and harvesting dates, tillage practices, etc. The agricultural management scenario for the study was adapted from the crop rotation and management scenarios (OCMS) for the Olentangy River Watershed TMDL study (Witter, 2006). The OCMS provided an exhaustive description of the combination of different management practices such as crop rotation, planting date, amount and timing of fertilizer and manure application, tillage types, harvest date etc. Since both watersheds receive more or less similar agricultural management practices, OCMS was used in this study with necessary modifications using farm survey based information from UBWC. Generally, in SWAT analysis, agricultural management is limited to two or three management scenarios with two to three years of crop rotation repeated over the simulation period (Hu and McIsaac et al., 2007). However, this approach may not fully capture the temporal changes in crop areas, tillage, and other management options that might actually occur in the watershed during the simulation period. Therefore, the present study considered 20 agricultural management scenarios described over 16 years to capture the changes in management options during the simulation period. The cropping rotations considered were, corn-soybean, corn-soybean-soybean and corn-soybean-wheat (any combination of these may occur in any of the 20 management scenarios). Planting and harvest dates were selected based on cumulative density functions (CDFs) created from county-based agricultural statistics data (Fig. 2.2) reported by the Ohio Agricultural Statistics Service. Several points on the CDF were selected to represent a good distribution of planting dates. Following Witter (2006), percent of planting associated with each one of those days was estimated by finding the difference between the midpoints of planting date and the prior and/or following planting date.

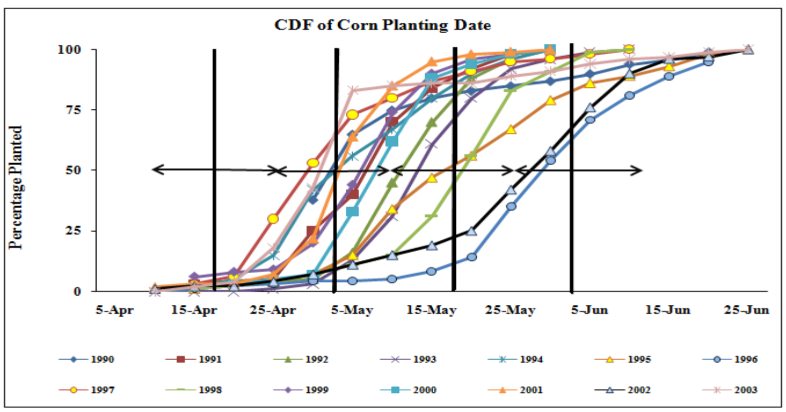

Fig. 2.2 Cumulative density functions of corn planting date derived for each year (Source: NASS data, 1990-2003).

SWAT assumes that plants start growing immediately after planting, without considering the heat unit required for crop emergence (Baumgart, 2005). However, corn requires about 100 growing degree days to emerge (Thomison, 2009). To account for the time taken for crop emergence after planting, planting dates were delayed approximately 7-10 days from the estimated planting dates (Baumgart, 2005). Timing of management operations were fixed relative to the planting date, which allowed sufficient variations in timing of management operations across the watershed. In this way, several scenarios with varied management operations were used in the study to replicate the actual management practices occurring in the watershed. Rate of nitrogen and phosphorous application (N:P) for corn (168 kg/ha: 67.2 kg/ha), soybean (16.8 kg/ha: 56 kg/ha) and wheat (84 kg/ha: 56 kg/ha) were based on Tri-State Fertilizer Recommendations (Vitosh et al., 1995). In addition, split application of nitrogen for corn (112 kg/ha at planting followed by 56 kg/ha as side dressing after a month) was also included in the 20 management scenarios. Information on tillage practices was taken from the results of surveys conducted by the Conservation Technology Information Center (www.ctic.purdue.edu/CTIC/). The timing of fertilizer application and tillage operations were obtained from a farm survey and expert opinion. Even though nutrient loads from agriculture vary with management practices (Kannan, 2007), the management practices applied to SWAT were not subjected to a systematic comparison with the actual agricultural management in the watershed during the same period. Therefore, this study evaluated the different management inputs assigned to the SWAT model for the simulation period with the actual management practices in the watershed. Thus, the allocations of the different management scenarios within agricultural HRUs were selected to adequately represent existing management practices and areas under different crops, tillage and fertilizer application. The allocation of management practices in SWAT was able to capture the temporal variability in major management practices that determine nutrient loading such as, cropped area, N application and tillage practices for each crop (Fig. 2.3 & 2.4). Results of paired t-test showed no significant differences ($P>0.05$)

between management practices applied in SWAT and actual management practices in the watershed (Table2.2).

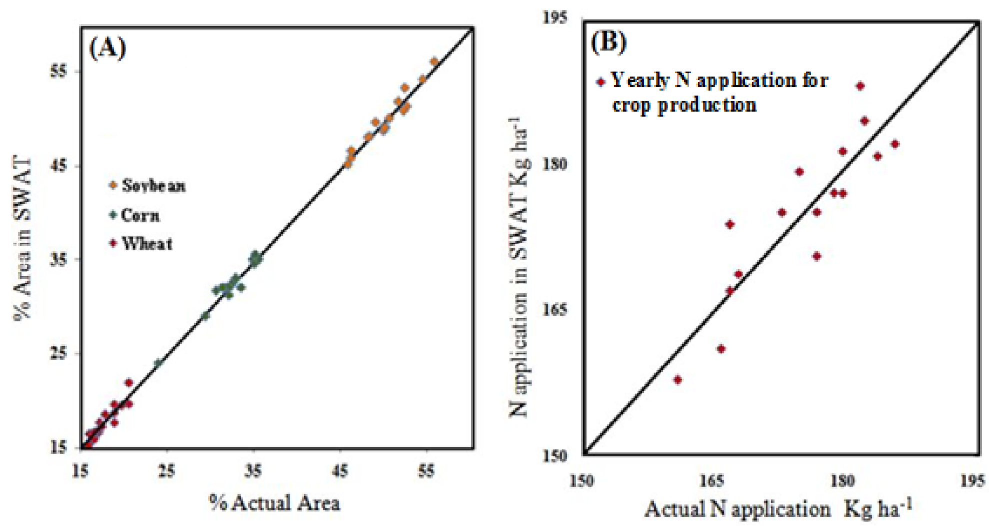

Fig. 2.3 Percentage area under corn, soybean, and wheat (A) and N fertilizer application (B) in SWAT and in watershed during simulation period.

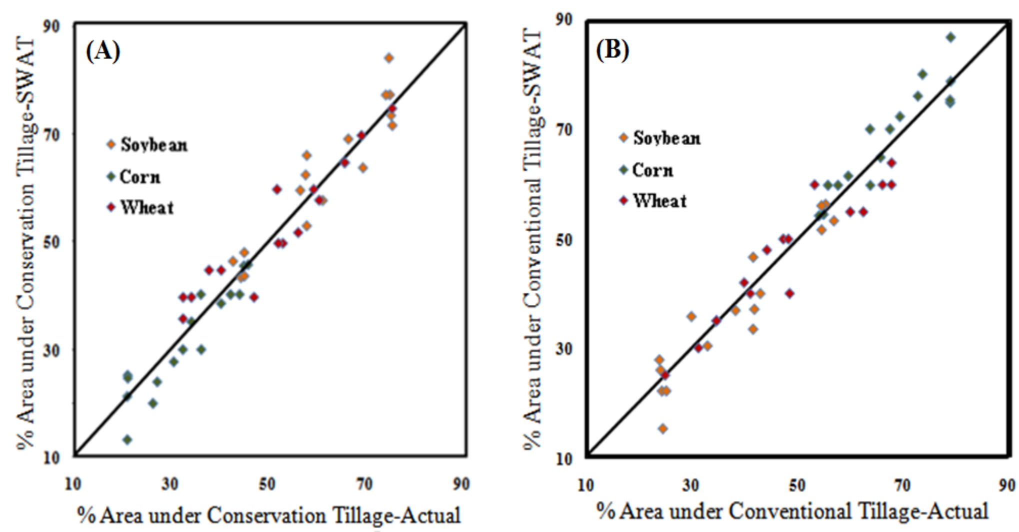

Fig. 2.4 Percentage area under conservation tillage (A) and conventional tillage (B) for corn, soybean and wheat in SWAT and in watershed during simulation period.

Management Practices	t-test (t critical = 2.13)
Crop Area	
• Corn	0.61
• Soybean	0.38
• Wheat	0.14
Conservation Tillage	
• Corn	1.66
• Soybean	1.03
• Wheat	0.98
Conventional Tillage	
• Corn	1.52
• Soybean	1.36
• Wheat	0.92
N Fertilizer	0.38

Table 2.2 The t test of management practices in SWAT and in the watershed.

2.2.5 Initial parameter configurations

During the process of characterization of a given watershed, SWAT assigns default parameter values for all the structural variables in the model. However, if available it is desirable to adjust or/ and change the default parameter values to match watershed specific values (Hu and McIsaac et al., 2007). The parameters that were specified based on the physical conditions of UBWC are given in Table 2.3. These parameters were not further adjusted during the calibration procedures. In addition, many of the naturally existing vegetative buffers and buffers installed as an outcome of on-going conservation efforts were not represented in the land cover map used for the study.

Therefore, the information regarding extent of existing buffers were derived from orthophotos of the Delaware and Morrow counties and incorporated in the model.

Parameter name and physical meaning	**Original value**	**Adjusted value**	**References**
SMFMX - The maximum snow melt factor	4.5	2.5	Neitch et al., 2002
SMFMN - The minimum snow melt factor	4.5	2.5	Neitch et al., 2002
CH_N(1) - Manning's coefficient for the tributary channel	0.014	0.05	Chow et al., 1959
BLAI - Maximum potential leaf area index	3	3.5	Thomison, 2008
SLSUBBSN - Average slope length	30 % of original value		Witter, 2006
RNC - Concentration of nitrogen in rainfall	1 ppm	2ppm	Brown, 1994

Table 2.3 Adjusted parameters before calibration based on the information of the watershed.

2.3 Model calibration and validation

2.3.1 Data used for calibration and validation

Daily stream flow data from the USGS gage stationed within the UBWC watershed at Sunbury (site no. 03228300) were obtained for the period of 1990 to 2005, of which data from 1990-1995 were used for calibration and data from 1996-2005 were used for validation of the model. County level corn, soybean and wheat yield estimates for 1990-2005 were obtained from USDA-NASS (2008) for the five counties that the watershed spans (Delaware, Morrow, Knox, Licking and Franklin). The temporal area data for corn, soybean and wheat by county was used as a weighing factor to determine watershed scale crop yield. Simulated crop yields were in tons of dry-weight per hectare, which were converted to bushels per acre of wet-weight using relationships outlined by Gassman (2008). The calibration of total nitrogen (TN) loading from the watershed was accomplished by using measured TN concentrations from two experimental paired headwater sub-watersheds in UBWC for the year 2005. The selected paired watersheds were already validated for the future assessment of conservation practices (King et al., 2008). From each of the experimental pair of watersheds, TN loading data from one of the sub-watersheds was used for calibration and the other was used for validation.

2.3.2 Assessment of calibration and validation of the SWAT model

Model performance was evaluated using two commonly used error measures in modeling, Nash-Sutcliffe coefficient of efficiency (E) (Nash and Sutcliffe, 1970) and the linear regression coefficient of determination (R^2), which were calculated as follows:

$$E = 1 - \frac{\sum\left(\hat{X}_i - \bar{X}_i\right)^2}{\sum(X_i - \bar{X}_i)^2}$$

$$R^2 = \frac{\left[\sum\left(\hat{X}_i - \bar{\bar{X}}_i\right)(X_i - \bar{X}_i)\right]^2}{\sum\left(\hat{X}_i - \bar{\bar{X}}_i\right)^2 (X_i - \bar{X}_i)^2}$$

where $\hat{X}_i$, X_i , $\bar{\bar{X}}_i$ and $\bar{X}_i$ are simulated, observed , mean of simulated and mean of observed values respectively.

The E values vary from 1 to negative infinity and show the one to one comparison of the observed and simulated data with a line of slope 1 and intercept of 0. Values near 1 show significant agreement with observed data. Values near zero or less imply that the average value of the observed data is more reliable than the model prediction (Legates and McCabe, 1999). The R^2 value displays the ability of model predictions to explain the variance in the measured data and can have any values from 0 to 1. The predicted and measured data show no correlation when R^2 equals to 0 and dispersion of the predicted and measured data become equal when R^2 equals 1 (Krause et al., 2005). Moriasi et al. (2007) proposed a threshold E value of >0.5 for judging monthly calibration of SWAT for water quality application. Considering Moriasi et al. (2007) recommendation, E values of 0.4 (daily), 0.5 (monthly) and 0.7 (annual) were considered as criteria for judging daily, monthly and annual time steps, respectively, for hydrologic and nutrient loading simulations (Table 2.4). The same threshold values were used to judge the model's performance for R^2 (Gassman, 2008). However, calibration of crop yield was attempted to achieve the highest possible E and R values.

Error measures	Simulation Time Step		
	Daily	Monthly	Annual
Nash-Sutcliffe Efficiency (E)	> 0.4	> 0.5	> 0.7
Coefficient of determination (R^2)	> 0.4	> 0.5	> 0.7

Table 2.4 Criteria used for analyzing the model performance for hydrology and nutrient loading.

2.3.3 Calibration procedure applied for the study

In general, SWAT calibration starts with stream flow, followed by sediment and nutrients (Arnold et al., 2000; Santhi et al., 2001; Kirsch et al., 2002). Even though crop growth is the prime driver of water and nutrient balance in a watershed, calibration of the

SWAT crop growth component has rarely been reported (Baumgart, 2005). Interestingly, the standardized SWAT calibration and validation procedure in SWAT manuals do not discuss the need for crop yield calibration (Neitsch et al., 2002). Water quality modeling efforts generally focus only on stream flow, rather than evaluating all possible components of SWAT hydrology and nutrient cycling, for example crop growth, which in turn drives the water balance and nutrient balance of a watershed (Kannan et al., 2007). A few studies have adjusted crop parameters as a part of hydrologic or nutrient calibration and indirectly tested the crop sub-model. Baumgart (2005) attempted calibration and validation of the SWAT crop sub-model using county level crop yield data. Hu et al. (2007) calibrated the SWAT crop components while applying SWAT to water quality concerns in an eastern Illinois watershed and reported that simulated crop yields within 10% of observed data. Kannan et al. (2007) used externally calculated heat units and published crop growth parameters including maximum leaf area index (LAI), canopy height and root depth for hydrologic calibration of SWAT and reported that the changes made in crop parameters substantially improved the simulation. However, this study did not provide any information about the impact of these changes on crop biomass production and crop yield. In addition, Gassman (2008) attempted a comprehensive analysis on SWATs crop model for corn and soybean production in Iowa and suggested that for accurate regional crop yield prediction, adjustment of generic crop parameters would be essential. Pohlert et al. (2005) further explored internal drivers of nutrient balance and reported unexpected behavior of denitrification and plant nutrient uptake just after fertilizer application, but this study did not report relationships to crop parameters. In agricultural or rural watersheds like UBWC, accurately representing crop water use and nutrient uptake are critical for interpreting the hydrology and nutrient balances. Thus, it is advisable to calibrate the crop sub-model first, followed by stream flow, sediment, and nutrients for agricultural watersheds. Unfortunately, data needed for a detailed crop sub-model calibration, include among others changes in biomass and LAI, over the growing period. Unfortunately these data are not readily available; however crop yield is often reported. For economic evaluation of alternative conservation practices for nutrient load from agricultural land, crop yield is one of the major economic variables. Calibration of the crop sub-model based on measured crop yield should be required. Thus a comprehensive calibration approach was designed with four distinct stages (Fig. 2.5). During stage-1, sensitive parameters were selected for calibration and default values of the selected parameters were changed with a value within the range based on SWAT literature (Neitsch et al., 2002; Arnold et al., 2000; Santhi et al., 2001; Baumgart., 2005; Hu et al., 2007; Kannan et al., 2007; Gasssman, 2008) or expert opinion. Next stage, calibration of hydrology and processes driving the water balance were attempted followed by crop yield and biomass calibration and TN loading calibration. Each stage was linked backward and forward to achieve criteria set for calibration.

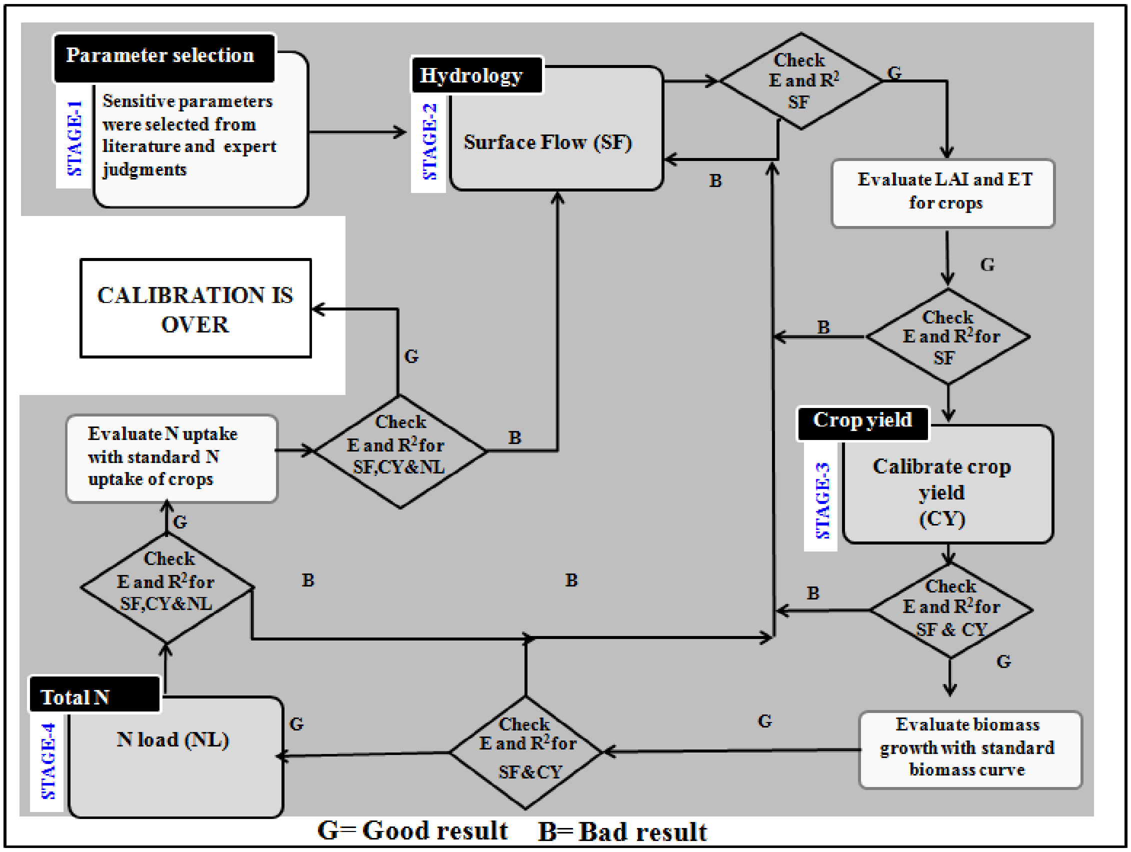

Fig. 2.5 Comprehensive calibration approach attempted in study.

Thirty parameters under hydrology, crop, nutrient cycling and sediment sub-routines of the model were adjusted during the calibration process. Without calibration (base-run), simulated total stream flow for the period of 1990-1995 was overestimated by 10.41% compared to the measured value at USGS gage. It was also found that the stream flow during summer months was consistently over-predicted with under-prediction of actual ET during summer. Thus, the primary focus of the hydrological calibration was to reduce the predicted stream flow and correspondingly increase the values of other components that drive the hydrology. Hydrologic calibration parameters are presented in Table 2.5.

	Original value	Calibrated value
PET method	Penman/Monteith	Hargreaves
Hydrology Parameters		
EPCO – Factor that allows model to use water in the lower layer of soil to meet plant transpiration demand	1	0.95
ESCO – Factor that allows model to use in the lower layer of soil to meet soil evaporation demand	0.95	0.98
FFCB – Initial water storage in soil	0	0.78
ICN – Switch for updating CN # based on ET	0	1
CNCOEF – Weight used for ET to update CN	1	0.88
ALPHA_BF – Baseflow factor	0.048	0.02
CN # – Curve number	Initial value	Reduced by 10%
SURLAG – Surface runoff lag coefficient	4	1

Table 2.5 Parameters adjusted during the calibration of hydrology.

The default PET calculation method, Penman/Monteith method (Monteith, 1965), was replaced by Hargreaves PET method (Hargreaves et al., 1985). Subsequently the model estimated actual ET for summer months was 484mm, which was comparable to the reported summer months actual ET of 464mm for corn and 432 mm for corn and soybean, respectively, in the nearby region (Allred et al., 2003). Additionally CN was adjusted daily based on plant ET rather than available moisture capacity. ET weighing factor (CNCOEF) used to adjust CN was fixed as 0.88. Thus, the model would update the CN value to a lower level whenever ET dominates the hydrologic regime, permitting more infiltration during the summer months. As the simulation started in winter months, the initial soil water storage fraction (FFCB) parameter was set to 0.78 (Witter, 2006). Moreover, the CN2 was decreased by 10% for all HRU's except for those with sub-surface drainage. A decrease in CN2 makes the surface more permeable, which in turn enhanced the water movement into the soil profile. The SOL_AWC was increased by 20% to augment the water storage in the soil profile, so that the water entering the soil would be available for crop use. Furthermore, base flow parameter, Alpha_BF was also reduced from 0.048 to 0.02 based on an analysis of USGS stream gage data and a baseflow separation program (Arnold et al., 1995; Arnold and Allen, 1999). Subsequently, the ESCO and EPCO parameters were adjusted to better represent crop ET demands. To address event timing, the parameter that controls the water movement from land surface to adjacent reach over days after the precipitation (lagged runoff), SURLAG was changed. After evaluating the regression results of lagged rainfall days (up to 7 lag days) against the measured stream flow at the USGS gage, SURLAG was assigned a value of 1.

A summary of the average annual water balance with the calibrated model is presented in Table 2.6 along with the average annual water balance for the state of Ohio (Brown, 1994). The Spearman rank analysis showed that predicted water balance is not significantly different from average Ohio water balance.

Component of hydrologic cycle	Average water balance for Ohio (depth of water in mm)	Predicted Water Balance[1] (depth of water in mm)
Precipitation	965	1075.5
Actual ET	508	701.5
Surface runoff	254	268.22
Ground water flow	51	75.77
Total Aquifer Recharge	102	105.37
Stream discharge	305	352.77

1-Averages taken from Brown (1994)

Table 2.6 Model predicted annual average annual water balance for UBWC watershed and the statewide average for Ohio.

The monthly hydrographs for the calibration and validation periods are given in Figs. 2.6 A and B. Predicted stream flow consistently matched with the observed stream flow. Additionally, the timing of the predicted runoff events also followed the observed timing. However, several discrepancies in peak flow predictions were noted, especially for validation period. Underestimation of peak flow by SWAT has been reported by several researchers (e.g. Fohrer et al., 2001; Chanasyk et al., 2003; Bosch et al., 2004; Chu and Shirmohammadi, 2004; Du et al., 2005). The model efficiency calculations showed that the calibrated model met all the criteria set for the evaluation of the model. In addition, intercepts of regression were not significantly different from zero and slopes of regression were not significantly different from one for monthly and annual time steps (Table 2.7).

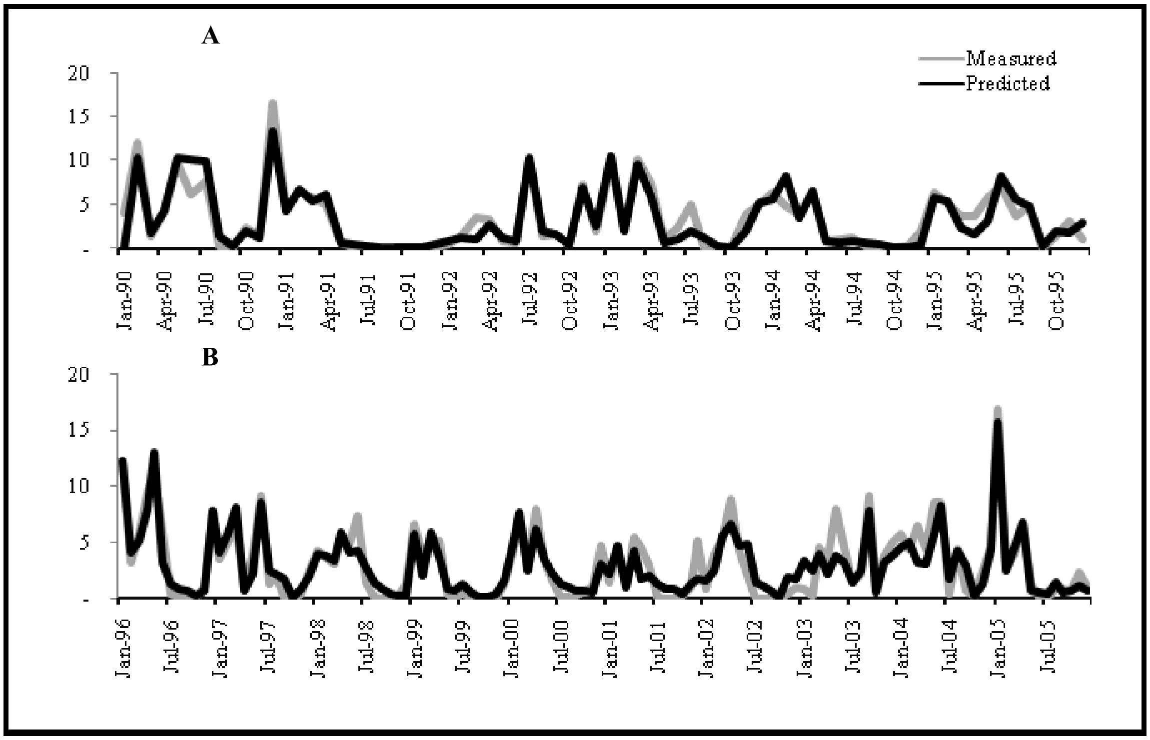

Fig. 2.6 Calibration (A) and validation (B) of stream flow.

Time Interval		E	Regression					
			R^2	Intercept	SE	Slope	SE	F value
Daily	Calibration	0.68	0.68	0.41***	0.11	0.75	0.01	45.61
	Validation	0.50	0.51	0.52***	0.10	0.58	0.01	84.16
Monthly	Calibration	0.85	0.86	0.36	0.21	0.83	0.04	1.04
	Validation	0.86	0.85	0.02	0.16	0.82	0.04	1.01
Annual	Calibration	0.98	0.97	-0.05	0.29	0.92	0.09	0.39
	Validation	0.87	0.87	0.09	0.42	0.86	0.14	0.01

*** Significant at 0.01

Table 2.7 Performance of hydrological modeling.

To ensure crop water usage over the growing season was modeled correctly, ET and LAI distribution over the growing period for corn, soybean and wheat for a randomly selected HRU and year was analyzed (Fig. 2.7). It is evident that the inter-link between LAI and ET was simulated properly by the calibrated model as ET increased with increase in LAI and dropped when LAI started declining. So the simulation results demonstrated that the calibration effectively addressed the crop water usage component of the watershed water balance.

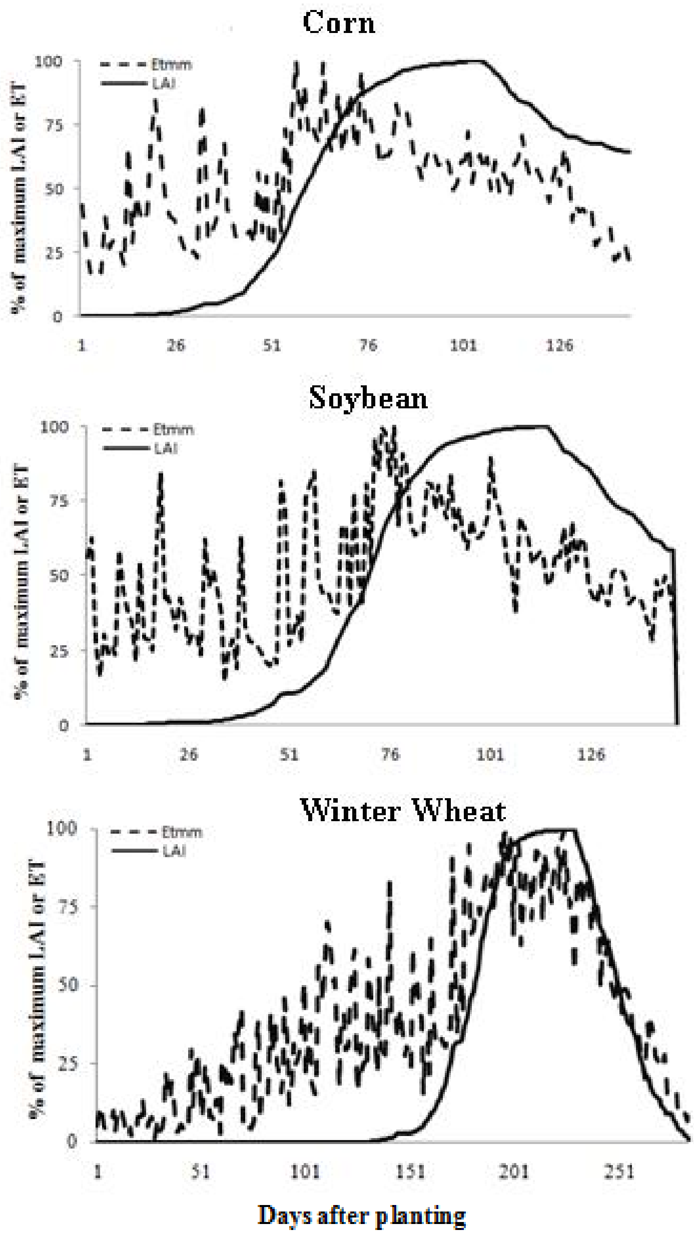

Fig. 2.7 Simulated evaporation/transpiration (mm) and LAI for corn, soybean and winter wheat.

Potential plant growth, i.e. plant growth without any abiotic and biotic stress, was simulated daily using radiation use efficiency (BE) and photosynthetic active radiation.

BE is the amount of dry biomass produced per unit intercepted photosynthetic active radiation (Neitsch et al., 2005). SWAT crop yield was expressed as the harvestable fraction of the cumulative biomass produced over the growing season, and the harvestable fraction was defined by two factors, fraction of the above ground biomass on the day of harvest and the harvest index.

	Original Value	Calibrated value
Crop parameters		
BE		
CORN	35	30
SOYBEAN	25	20
WINTER WHEAT	30	25
Harvest Index		
CORN	0.50	0.45
SOYBEAN	0.31	0.27
WINTER WHEAT	0.40	0.35
LAI		
CORN	3.0	3.5
SOYBEAN	3.0	2.0
WINTER WHEAT	4.0	3.0

Table 2.8 Parameters adjusted for crop yield calibration.

Simulated crop yields for all the three crops were consistently higher than reported regional yields. However, temporal variability in yield was captured to some extent by the crop sub-model. Therefore further calibration was focused on lowering the predicted yield. Following Baumgart (2005), BE was lowered to calibrate crop yield. The corn BE was reduced to 30 from 35, soybean BE was decreased to 25 from 20 and BE for wheat was fixed at 25 instead of 30. Additionally, maximum potential LAI was changed to 3.5, 2 and 3 for corn, soybean and wheat, respectively, while harvest index was adjusted to 0.45, 0.27 and 0.35 for corn, soybean and wheat respectively (Table 2.8). Average annual yield for corn, soybean and wheat are reported in Table 2.9. The predicted average yield for corn, soybean and wheat for calibration and validation periods were not significantly different ($P > 0.05$) from reported yields for the watershed. Moreover, the annual predicted yield for corn, soybean and wheat were also comparable with the reported yield in the region (Fig. 2.8).

Crop		Crop Yield (bushels per acre)		t-Value[1]
		Reported	Modeled	
Corn	Calibration	118.04	113.95	0.73
	Validation	126.93	125.20	0.52
Soybean	Calibration	39.40	40.47	0.95
	Validation	40.63	41.55	0.91
Winter Wheat	Calibration	54.95	55.70	0.59
	Validation	62.42	66.11	2.04

[1]*Critical 't' value for calibration is 2.57 and validation is 2.26*

Table 2.9 Average reported and simulated crop yields.

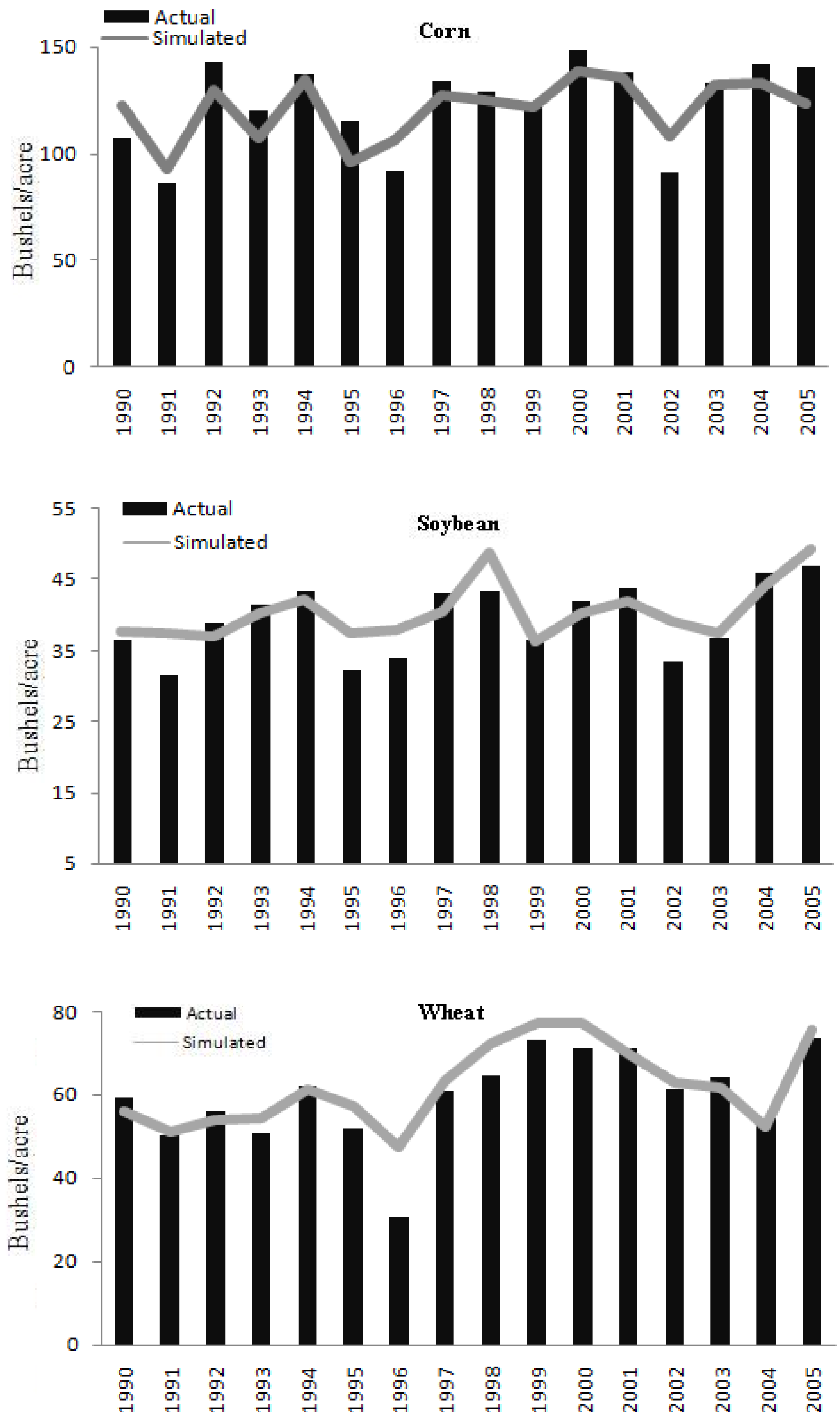

Fig. 2.8 Model predicted and observed yield for corn, soybean and wheat in the Upper Big Walnut Creek watershed.

The reported yields for all the crops showed a considerable variation between calibration and validation periods, which was captured well by the model. Corn yields were simulated well during calibration and validation periods with E values of 0.51 and 0.54 respectively. Results for soybean and wheat yields were more significant than corn yield, especially during the validation period. In addition, intercepts of regression were not significantly different from zero and slopes of regression were not significantly different from one except for corn in validation period (Table 2.10).

Time Interval		E	Regression					
			R^2	Intercept	SE	Slope	SE	F-Value
Corn	Calibration	0.51	0.58	17.15	43.23	0.88	0.38	0.09
	Validation	0.54	0.88	-87.53***	27.98	1.71	0.22	10.25
Soybean	Calibration	0.52	0.62	-33.72	27.95	1.84	0.72	1.03
	Validation	0.69	0.61	4.59	10.24	0.87	0.24	0.29
Winter Wheat	Calibration	0.53	0.57	-0.99	24.24	1.01	0.44	0.00
	Validation	0.61	0.81	-10.55	12.71	1.11	0.19	0.24

*** Significant at 0.01

Table 2.10. Efficiency criteria for crop yield calibration.

In an agricultural watershed, calculation of crop yield is important to the overall N balance. Crops consume a major portion of applied N or add N by biological N fixation (e.g. soybean). One part of the N taken by the crop is lost from the watershed as harvested yield and the other portion would return back to the soil as crop residue. These N output and input sources have to be considered while calibrating N loading. Crop yield in the model is defined as the fraction of above ground biomass removed during the harvest and the fraction is defined by harvest index. So calibration of the crop yield is accounted for during calibration of biomass production. Crop N demand throughout the growing season of a plant was calculated in the model using growth-stage specific N uptake parameters, PLTNFR-1, PLTNFR-2 and PLTNFR-3 representing N uptake by the plant at emergence, at 50% maturity and at full maturity. N uptake parameters were adjusted for calibrating N uptake by crops. It was found that the predicted biological N fixation by soybeans was very high (on an average >240 kg ha^{-1} N), which was also reported by many researchers (Hu et al., 2007; Gasssman, 2008). So PLTNFR-1, PLTNFR-2 and PLTNFR-3 were reduced to decrease the N demand by the soybean, which resulted in a lower N fixation by soybean compared to initial simulation results. Additionally, the amount of N removed by the crop yield was achieved by calibrating the fraction of N in yield parameter (CNYLD) (Table 2.11).

Parameter	Original Value	Calibrated value
CNYLD		
• CORN	0.0140	0.0125
• SOYBEAN	0.0650	0.0500
• WINTER WHEAT	0.0250	0.0250
Nitrogen uptake parameter #1:		
• CORN	0.0140	0.0125
• SOYBEAN	0.0650	0.0500
• WINTER WHEAT	0.0250	0.0250
Nitrogen uptake parameter #2:		
• CORN	0.0470	0.0370
• SOYBEAN	0.0524	0.0400
• WINTER WHEAT	0.0663	0.0463
Nitrogen uptake parameter #3:		
• CORN	0.0138	0.0115
• SOYBEAN	0.0258	0.0188
• WINTER WHEAT	0.0148	0.0108
N-Cycling		
CMN	0.0003	0.0002
NPERCO	0.2000	0.8500

Table 2.11 Crop parameters adjusted for N calibration.

Fig. 2.9 shows the simulated N uptake and biomass accumulation over the growing period for corn, soybean and wheat for a randomly selected HRU and the standard N and biomass accumulation graph for the respective crops. The partitioning of biomass and N uptake modeled by SWAT corresponded well with the standard biomass and N accumulation curve for the respective crops.

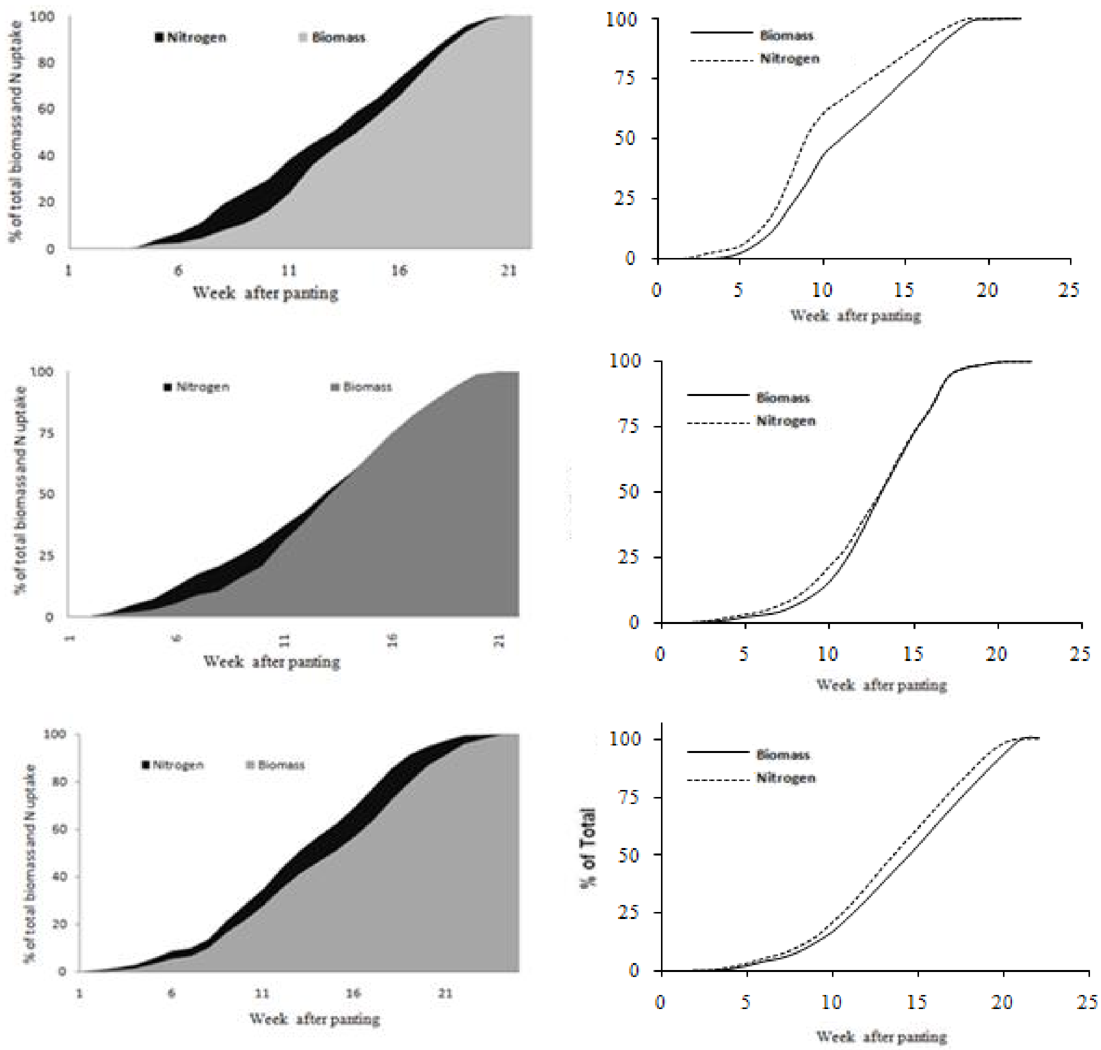

Fig. 2.9 Comparison of modeled N and biomass accumulation for corn, soybean and wheat with the standard N and biomass accumulation curves.

In addition to the crop parameters, two other nitrogen nutrient cycling parameters namely, humus mineralization coefficient (CMN) was reduced and the coefficient for N percolation (NPERCO), was increased from the default values to obtain better calibration. Observed monthly nitrate loads for both the calibration and validation periods for two experimental paired watersheds in the UBWC watershed are given in Fig. 2.10.

Paired watershed		E	Regression					
			R^2	Intercept	SE	Slope	SE	F Value
Pair - 1	Calibration	0.73	0.87	-.58	0.74	1.44***	0.18	6.38
	Validation	0.65	0.66	-0.39	0.64	1.09	0.25	0.13
Pair - 2	Calibration	0.80	0.86	-0.36	0.31	0.94	0.11	0.28
	Validation	0.65	0.77	0.46	0.34	0.46***	0.09	3.28

*** Significantly different from 1 based on F value

Table 2.12 Efficiency measures for TN calibration.

For the calibration and validation periods, efficiency E values were 0.73 and 0.65, respectively, for the first set of paired watershed, and 0.80 and 0.65, respectively for the second set of paired watershed. In addition, intercepts of regression were not significantly different from zero in calibration and validation. Moreover, slopes of regression were not significantly different from one except for corn in validation period (Table 2.12). However, slopes of the regression were not significantly different from one in two cases, calibration period in Pair-1 and validation period in Pair-2. All values were similar to the reported E value for nitrate load in previous SWAT studies (Chaplot et al., 2004; Santhi et al., 2001).

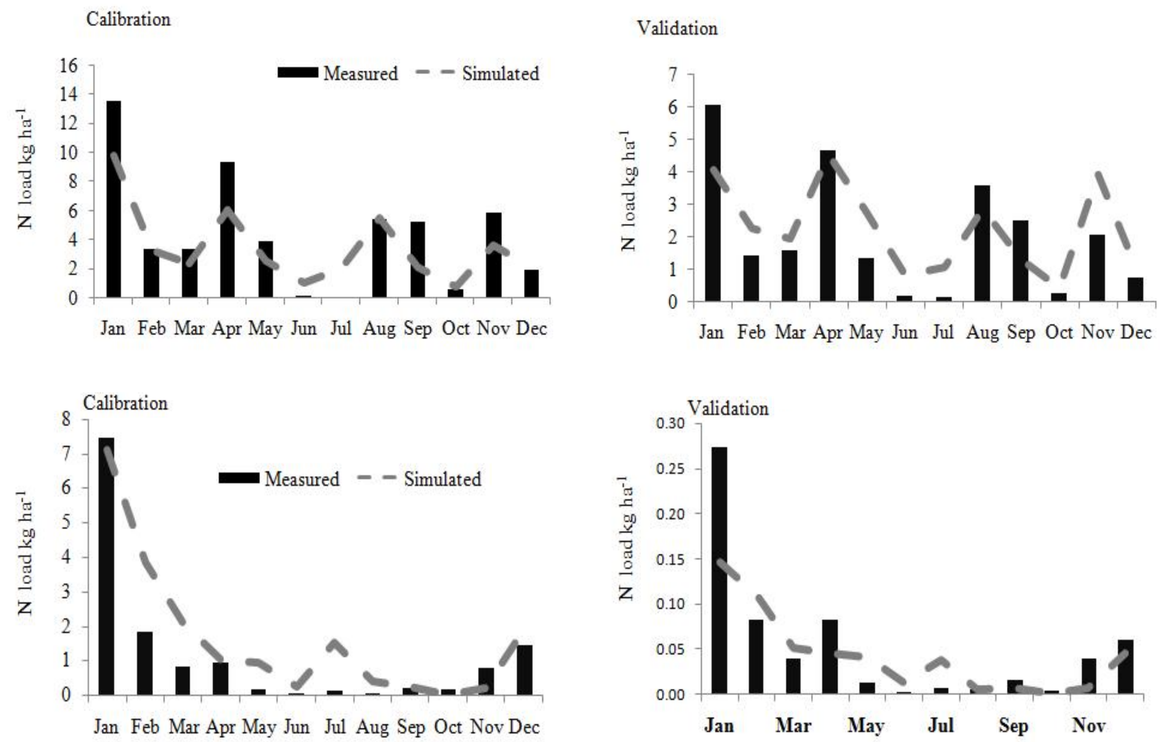

Fig. 2.10 Simulated and observed total N loading from two paired watersheds in Upper Big Walnut Creek watershed.

In all four graphs, maximum TN load occurs during the winter season. This can be attributed to both the lack of N uptake by plant and high snowmelt runoff during winter season. Comparisons in the hydrology and TN calibration suggest that the processes driving the water and N balance in the UBWC watershed were appropriately modeled and that this model set up can be used for modeling management strategies to reduce N loading from the watershed.

2.3.4 Uncertainty Analysis

During calibration, model parameters were adjusted deterministically to more accurately predict measured values. However, in nature these parameter values are stochastic. Uncertainty analysis is one way to assign stochastic changes to parameters with fixed values. So, uncertainty analysis would be useful to understand the robustness of model when model parameters are subjected to stochastic changes (Haan, 2002; Chaubey and White, 2005). Thus an uncertainty analysis was performed on sensitive hydrology and TN prediction parameters. Uncertainty analysis is carried out as follows:

1. Sensitivity analysis of model parameters
2. Generate probability density function (PDF) for sensitive parameters
3. Replace parameter values by values from PDF
4. Quantify uncertainty

1. Sensitivity analysis of model parameters

In general, sensitive model parameters are selected for uncertainty analysis (White and Chaubey 2005; Migliaccio and Chaubey, 2008). Sensitivity analysis could indicate the influence of model parameters on monthly stream flow and TN loading. Based on existing SWAT literature, parameters were selected for sensitivity analysis (Sohrabi et al., 2002; Sohrabi et al., 2003; Migliaccio and Chaubey, 2008; Shen et al., 2008). Sensitivity is defined as percent change in output due to one percent change in parameter value,

$$\text{Sensitivity } (\square) = \frac{\left(\frac{\Delta y}{y}\right) \times 100}{\left(\frac{\Delta x}{x}\right) \times 100} = \frac{\Delta y}{\Delta x}\frac{x}{y}$$

where Δ□ is change in parameter value, Δ□ is change in output value, □ is initial parameter value and □ is initial output value (Haan, 2002). Any parameter with an S values ≧ 0.05 (at least 0.05 % change in output value when parameter value is changed by 1 %) were selected for uncertainty analysis.

Parameter	**Parameter definition**	**S of stream flow**	**S of TN**
		Hydrologic factors	
Alpha_BF	Baseflow alpha factor	0.0014	< 0.0058
GW_DELAY	Groundwater delay time	< 0.0004	< 0.0097
GW_QMN	Threshold depth of water in the shallow aquifer required for return flow to occur	<0.0001	< 0.0058
G W_REVAMP	Groundwater revap coefficient	**0.0578**	< 0.0203
CNCOEF	ET weighting factor for CN# update	0.0100	< 0.0391
ESCO	Soil evaporation compensation factor	**1.4700**	**1.0544**
EPCO	Plant evaporation compensation factor	0.0015	0.0191
SURLAG	Surface runoff lag coefficient	0.0007	< 0.0214
FFCB	Initial soil water content	0.0054	0.0020
SOL_AWC	Available soil water	**0.1150**	**2.3681**
CN#	Initial SCS runoff curve number	**0.4850**	**5.2628**
		N Balance factors	
CMN			**0.1257**
NPERCO			**-0.1935**

Table 2.13 Parameters evaluated in SWAT sensitivity analysis.

Sensitivity analysis indicated that all selected parameters have influence on stream flow and TN load predictions (Table 2.13). However, only 4 hydrology parameters, CN, ESCO, SOL_AWC, and GW_REVAMP with S value > 0.05 were selected for uncertainty evaluation. In the case of TN loading predictions, CN, ESCO, SOL_AWC, CMN, and NPERCO were selected for uncertainty analysis. To account for the parameter's stochastic characteristics, Monte Carlo model simulations (MCS) were performed with using specified parameter distributions.

2. Generate probability density function (PDF) for sensitive parameters

The MCS is the most commonly used method for estimating uncertainty in watershed models (Wu et al., 1997; Shirmohammadi et al., 2001; Dubus and Brown, 2002; Shen et al., 2008). In addition, MCS is considered to be robust and the standard approach for quantifying uncertainty in water quality models (Hession et al., 1996; Yu et al., 2001). The appropriateness of the distribution selected for a parameter decides accuracy of output uncertainty estimates (Haan et al., 1998; Sohrabi et al., 2003). Even though there might be some level of correlation among the parameters selected, it is assumed that parameters are independent to one another because of lack of sufficient information to derive correlation among the parameters (Shen et al., 2008). Distribution used for MCS for parameters are given in Table 2.14. Distribution information for parameters such as ESCO, GW_REVAP, and AMP was scarce, so uniform distribution was assumed with range specified in the SWAT user's manual (Santhi et al. 2001; Sohrabi et al., 2003; Neitsch et al., 2005; Migliaccio and Chaubey, 2008). Meyer et al., 1997, derived distributions for available soil water content (SOL_AWC) based on texture of soil. This information was used for describing stochastic behavior of SOL_AWC. As distribution of CN is not readily available, distribution information of maximum soil moisture retention value (S), which is log normally distributed with a standard deviation of 0.5 times the mean of S (Haan and Schulze 1987), was used to derive stochastic variation in CN (Chaubey et al., 2003). The S value derived using CN values of calibrated model using following expression,

$$S = \frac{25400}{CN} - 254$$

For each parameter, randomly decided multiple runs (50-100) were made to generate PDF (with 5000 points) for each parameter.

Parameter	**Distribution**	**Reference**
ESCO	Uniform	Neitsch et al., 2005
GW_REVAMP	Uniform	Neitsch et al., 2005
SOL_AWC	Normal or lognormal	Meyer et al., 1997
S value of CN #	Lognormal	Chaubey et al., 2003
CMN	Uniform	Neitsch et al., 2005
NPERCO	Uniform	Neitsch et al., 2005

Table 2.14 Parameter-specific distribution for Monte Carlo model simulation.

3. Replace parameter values by values from probability density function

For each of the parameters, 10 values were selected from the PDF to limit number of simulations. However, the procedures followed for selection of these values were decided based on type of distribution. In the case of uniform distribution, PDF is sliced into 10 equal parts and from each part one value was selected randomly. But, for normal distribution (lognormal distribution also converted to normal) PDF was partitioned based on the standard deviation. The parameter value selections were based on following criteria.

- 6 values were selected from $\square + 1\square$ to $\square - 1\square$
- 1 value selected from $1\square$ to $2\square$ and $-1\square$ to $-2\square$
- 1 value selected from $> 2\square$ and $< -2\square$

4. Quantification of uncertainty

Uncertainty is defined as the variance of predicted value based on measured value (Radwan et al. 2003).

$$\text{Unceratnty } (\sigma^2) = \frac{\sum_{i=1}^{n}\left(Y_{\text{predicted } i} - Y_{\text{measured } i}\right)^2}{\square - 1}$$

where $\mathbf{Y}_{\mathbf{predicted\ i}}$ is simulated value and $\mathbf{Y}_{\mathbf{measured\ i}}$ is measured value.

To understand impact of uncertainty of individual parameters on stream flow and TN loading, simulations were made by changing single parameters with values from the PDFs. However, in reality all parameters would change simultaneously. So, in next step, each parameter value was randomly selected for simulation. The results of single parameter change showed that CN and ESCO are the parameters that can create much uncertainty in stream flow. Moreover, for CN, ESCO and SOL_AWC uncertainty and stream flow followed a quadratic relationship. Additionally, most of the points in the graph were located around the stream flow and uncertainty of calibrated model (Fig. 2.11 A). Uncertainty evaluated by randomly changing all selected parameters (Fig. 2.11 B), where stream flow corresponds to minimal uncertainty area close to calibrated value, indicates that model is robust in random shift in parameter values.

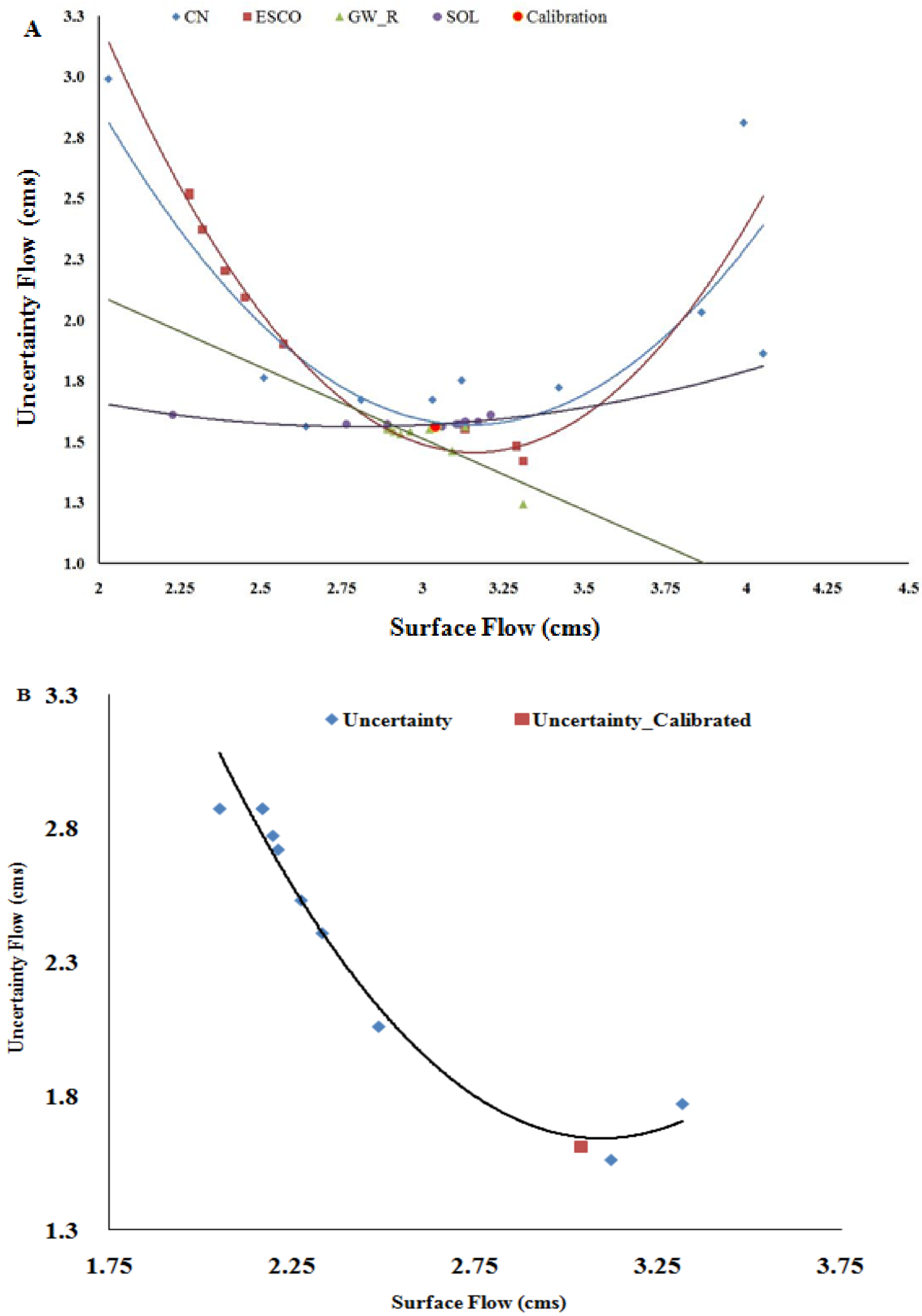

Fig. 2.11 Results of uncertainty analysis for stream flow: (A) Uncertainty in stream flow-changing single parameter, and (B) Uncertainty in stream flow-changing all parameter together.

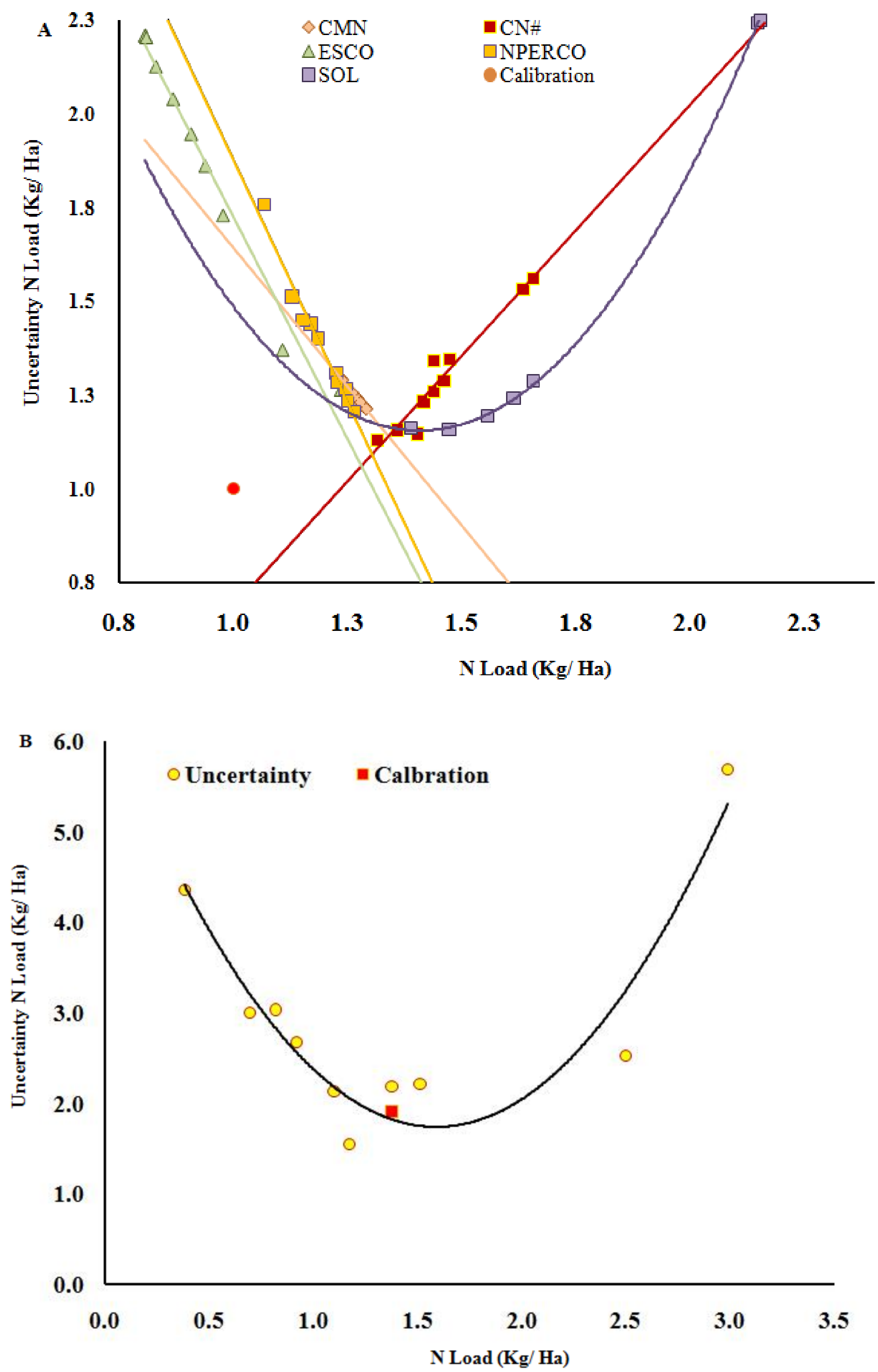

Fig. 2.12 Results of uncertainty analysis for TN: (A) Uncertainty in TN-changing single parameter, and (B) Uncertainty in TN-changing all parameter together.

The results of single parameter change showed that most of the parameters nutrient loading and uncertainty were linearly related expect for SOL_AWC. Additionally, for many of the parameters nutrient loading and uncertainly are negatively related. However, for parameter CN, TN loading uncertainty was positively related (Fig. 2.12 A). All points in the graph are located away from uncertainty for nutrient loading for calibrated model in the case of evaluation with single parameter at a time. However, when all the parameters were changed randomly together, nutrient load at minimal uncertainty is close to calibrated value (Fig. 2.12 B).

2.4 Conclusions

A comprehensive calibration approach by integrating hydrology, crop yield and N cycle together was attempted for SWAT modeling of UBWC watershed in central Ohio for a 6-yr period, and then validation of SWAT model for stream flow, TN load, and crop yields for a different 10-yr. The proposed approach has four distinct stages, starting with parameter selection, calibration of hydrology, crop yield and N cycling for evaluating SWAT modeling for water quality applications. Each stage was linked backward and forward to achieve the high efficiency for calibration together for stream flow, crop yield and TN loading. The inter-relationships between various processes under hydrology, crop growth and nitrogen (N) cycling in the SWAT model are explored further in proposed calibration method. Two major components water balance of a watershed, crop ET and stream flow were analyzed. The simulated ET was close to reported value in the region. The inter-link between LAI and crop ET were well established by the comprehensive approach, which resulted in simulated stream flow close to measured flow. The yield calibration for corn, soybean and wheat extended to evaluations of total biomass with standard biomass curves of the respective crop. The predicted crop yields were close to the reported yield value. The important components in watershed nitrogen balance, uptake of N by crop and TN load from the watershed were considered for calibration of TN. The inter-link between crop uptake of N and biomass growth were compared with standard crop N and biomass growth curve. Additionally, predicted TN load from the watershed was also close to the measured value. Moreover, uncertainty analysis of the sensitive parameters of the calibrated model revealed that stream flow and TN load predicted by calibrated model was with lower uncertainty value. The importance of proper modeling of major components of water and nitrogen balance and correct partitioning of water and nitrogen balance in an agricultural watershed for applying model for water quality analysis emphasized. The comprehensive calibration approach put forward by the paper underline the importance of exploring partitioning of water balance and N balance by SWAT simulation instead of traditional calibration of stream flow and TN load at watershed outlet.

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CHAPTER 3

ESSAY 2

RECREATIONAL VALUE OF WATER QUALITY IMPROVEMENT IN THE UPPER BIG WALNUT CREEK WATERSHED, OH.

3.1 Introduction

The travel cost method is a revealed preference (RP) approach that has been widely used in natural resource valuation research (Whitehead et al., 2000), specifically for estimating the economic benefits of outdoor recreation. With this method, the visitors have an opportunity to explicitly reveal their preferences through the site selection and number of recreational visits made to the site during a season. Thus, the RP based estimation rely on recall based data generation process, which could be considered as an *ex-post* analysis of recreational experiences of a paid visit (Martínez-Espiñeira, 2007). In addition to RP approach, stated preference (SP) method is also used for environmental economic analysis as a standalone method or in combination with RP. The SP approach uses hypothetical scenario based anticipated economic behavior of a visitor. Basically it is an *ex-ante* willingness to pay framework to generate the data (Whitehead et al., 2009).

The RP and SP approaches have been criticized, especially on their critical assumptions on the structure of preferences, which may not be testable always and data generation process followed (Adamowicz et al., 1994; Randall, 1994; Diamond and Hausman, 1994). However, it is claimed that combination of both the RP and SP, i.e., RPSP could overcome the limitations of the independent RP and SP methods, and synergize their advantages (Louviere et al., 2000). The standalone RP approach could address the economic valuation of a recreational site with current aesthetic and physical quality of the site. However, by applying RPSP, economic value of the recreational site with future changes in physical and aesthetic qualities could also be addressed. For example, the RPSP is suitable for evaluating the economic value of a recreational site with future improvements in water quality (Loomis, 1997; Whitehead et al., 2000).

Recently, accounting the effects of unobserved heterogeneity and state dependence together in recreational demand analysis received much attention, especially in discrete choice modeling (Bhat and Castelar, 2002; Boxall et al., 2003; Smith, 2005). The state dependence and unobserved heterogeneity in recreational decision making is closely related to Heckman's (1981) research on state dependence and heterogeneity in labor market. Heckman's definition of unobserved heterogeneity would also be applicable in recreational demand analysis. Thus, variation in the number of trips taken by respondents might be due to the dissimilarity in unobserved character of the visitors (visitor's taste over site characteristics). In contrast, state dependency exists in recreational demand setting when a past experience would make an authentic behavioral impact such that an individual with prior recreational experience in the same site would make a different recreational choice in future, compared to the one who doesn't have prior recreational experience. So, it could be argued that, in studies where anticipated future visits depend on baseline visit, the state dependence would become baseline dependence.

Bhat and Castelar (2002) applied unobserved heterogeneity and state dependence together in transportational choice analysis and showed that, if heterogeneity and state-dependence are not considered together in the modeling, that would result in biased estimates. Boxall et al. (2003) modeled a state dependence error structure to account for the state dependence and the correlation between RP and SP data, and observed that state dependence is empirically important in RPSP studies. Furthermore, Smith (2005) analyzed the implications of ignoring either state dependence or unobserved heterogeneity in fishing location choice analysis, and reported that state dependence is an important determinant for choice of location. All these studies are in discrete modeling framework using mixed loigt modeling.

Most RPSP studies in environmental economics did not consider state dependence and heterogeneity, and correlation between them in recreational data analysis. We are not aware of any previous research in the field of environmental economics that accommodated the effects of unobserved heterogeneity and state dependence together in continuous choice modeling framework, which is one of the focus of this study. In addition, the study also explores the change in recreational behavior of the visitors if they had enough information on current water quality impairment of the recreational site while they made their previous recreational trips. Generally, past studies evaluating water quality impact on recreational value focused on comparing the current recreational use-value with the anticipated recreational use-value under improved water quality scenario by using RPSP approach (Whitehead et al., 1998; Bhatt, 2003; Kragt et al., 2006; Paccagnan, 2007), with an implicit assumption that visitors had sufficient information regarding water quality of the site while they made their current visitation decision. However, most of the current visitors might not have the relevant information on current water quality impairment in the site while they made their recreational decision and this information gap might have impacted their recreational behavior.

Thus, the present study extends previous work on panel estimator with random effects (PERE) to combine RPSP in two counts: (i) exploring the impact of additional information on current water quality on current recreational decision making, and (ii) addressing baseline-dependence and unobserved heterogeneity in RPSP. The following section (section 2) briefly describes the problems related to the estimation of trip demand function and methodological approach used in the paper, whilst section 3 describes the survey design followed by results and discussion and some concluding thoughts.

3.2 Methodology

Before estimating the recreational demand parameters and deriving consumer surplus of the recreational trip, methodological challenges in trip demand modeling should be addressed. One of the issues in recreational demand analysis is the discrete and non-negative nature of the dependent variable. Additionally, most of the participants generally take small number of trips while a few participants take a large number of trips, therefore the recreational trip distribution is skewed to the left (Cameron and Trivedi, 2001; Martínez-Espiñeira, 2007). Furthermore, in mailed survey based research, some or many of the respondents might not have visited the site during the period specified in the survey (Shaw, 1988; Meisner and Wang, 2006). Thus, mailed survey data would be characterized by relatively higher frequency of zero observation, which often represents two different types of respondents. First, respondents who are not at all interested to visit the site, i.e. true non-participants. Second, respondents who might not have taken a trip to the site during the period specified in the survey, i.e. potential future visitor. Therefore potential future visitors do not have current (baseline) recreational experience at the site. However, in studies that combine RPSP to understand the changes in recreational behavior with future improvement in site quality, baseline recreational experience is important. In such studies, respondents were asked to provide details of not only the baseline trip to the site (RP) but also the probable future additional trips with changes in site quality or other trip decision variables (SP). As baseline visit is the last opportunity available to a visitor for updating the recreational experience from the site, respondents who made a recent visit to the site could easily connect current site quality and trip decision variables to possible future participation as compared to a respondent who doesn't have baseline experiences.

The structure preferences of the RP and the SP demand function needed to be tested for consistency before combing RP and SP data, which means that SP and RP demand functions must have the same structure of preferences to have consistent RPSP model (McConnell et al., 1999). In general, two methods are used for testing consistency of structural preferences in RPSP analysis, log-likelihood ratio based test (Swait and Louviere, 1993) and test for equality of demand parameters estimated from pooled data (Whitehead et al., 2000). The pooled test first estimates single demand function by pooling SP and RP data, and then the test for equality of parameters is performed, which allows flexibility of variation in underlying demand preference structure. Therefore this method is used for testing the structural preference of RP and SP demands in this study.

In RPSP studies, scenarios are sketches that make relative changes to relevant variable in baseline settings, for example 50% improvement in water quality, 20% increase in park entrance or 10% increase in gasoline cost. In this study, respondents were presented with questions on their baseline trips in 2008 and two scenarios-based anticipatory trips, which are described below:

1. Baseline trip: Number of visits made during 2008 recreational season.
2. Trip scenario-1: Probable change in baseline trips in 2008 recreational season, if information about the existing water quality impairments in the watershed is also available while making trip decision in 2008 recreational season.
3. Trip scenario-2: Anticipated additional trip in a typical recreational season, if all the streams and the reservoir in the watershed qualify EPA water quality standards.

Zero-inflated negative binomial (ZINB) is used in this study after initial testing of trip data for zero-inflation and over dispersion (details of the test results are given in

Appendix A). A ZINB model can be expressed as (Greene, 1994; Cameron and Trivedi, 1998):

$$f\left(y_{ij}=0\right)=\pi_{\mathrm{ij}}+\left(1-\pi_{\mathrm{ij}}\right)\times\left(\frac{k}{k+\mu_{ij}}\right)^{k} \tag{1}$$

$$f\left(y_{ij}|y_{ij}>0\right)=\left(1-\pi_{\mathrm{ij}}\right)\times\ f_{NB}(y) \tag{2}$$

The function $f_{NB}(y)$ is given as,

$$f_{NB}\left(y_{ij},k,\mu_{ij}|y_{ij}>0\right)=\frac{\Gamma(\mathrm{y_{ij}}+\alpha)}{\Gamma(\alpha)\times\Gamma(\mathrm{y_{ij}}+1)}\times\left(\frac{\alpha}{\alpha+\mu_{ij}}\right)^{\alpha}\times\left(\frac{\mu_{ij}}{\alpha+\mu_{ij}}\right)^{\mathrm{y_{ij}}} \tag{3}$$

Where $\mathrm{y_{ij}}\epsilon\{1,2,3,\ldots.\}$, k is the dispersion parameter of the NB, π_{ij} is zero-inflation probability and μ mean visit. Now we can extend the ZINB model to account or the baseline dependence and unobserved heterogeneity by adapting the approach proposed by Alfò and Aitkin (2006). As NB component of ZINB is accounting trip decision by visitor, baseline dependence and unobserved heterogeneity in modeling are explored in NB components of ZINB.

Let Y_{ij} is the trip taken by i^{th} visitor in j^{th} scenario, where $i=1,\ldots n_i$ of visitors in the data and $j=1,\ldots n_c$ scenarios. In other words, there are $j=1,\ldots n_c$ panels and $i=1,\ldots n_i$ individuals in each panel, so total number of observation is $n=\sum_i^{n_c}n_i$. Let $Y_{ij}=\left(Y_{i1},Y_{i2},\ldots\ldots Y_{in_i}\right)^T$ and x_{ij} are k number of known vectors of covariates associated with Y_{ij}. Here β is the $k\times1$ vector of parameters, x_{ij} is a $1\times k$ vector of explanatory variables for individual dimensional vector of regression parameters. To account for the unobserved heterogeneity across the individuals, a design vector $z_{\mathrm{ij}}^{\mathrm{T}}$ is defined, for each individual i z_{ij} is a two column vector of dummy variable and j. For example, if there are 3 panels in the dataset, then z_{ij} for individual i would be $z_{1\mathrm{j}} = \begin{bmatrix} 1 & 1 \\ 1 & 2 \\ 1 & 3 \end{bmatrix}$. Thus the size of $z_{1\mathrm{j}}$ would be matrices with $n \times j$ rows and $2 \times n$ columns. The model with random effects (RE) would be expressed as (Booth et al., 2003),

Logit part of ZINB

$$\log(\pi_{\mathrm{ij}}) = \gamma x_{\mathrm{ij}}^{\mathrm{T}} + \grave{\mathrm{e}}_{\mathrm{ij}} \qquad (4)$$

NB part of ZINB

$$\log\left(\mathrm{E}(\mathrm{Y}_{\mathrm{ij}} | x_{\mathrm{ij}}, \mathrm{b}_{\mathrm{i}})\right) = x_{\mathrm{ij}}^{\mathrm{T}}\beta + z_{\mathrm{ij}}^{\mathrm{T}}\mathrm{b}_{\mathrm{i}} + \mathrm{e}_{\mathrm{ij}} \qquad (5)$$

Logically, there would be some level of correlation between baseline visits, Y_{i0} and $\mathrm{b_i}$. This is because the persistent unobserved heterogeneity might have influenced the decision of Y_{i0} in a similar or dissimilar manner compared to anticipated future trips, Y_{i2} and Y_{i3} (Bhat and Castelar, 2002; Min and Agresti, 2005). Here, it is assumed that the correlation between unobserved heterogeneity and baseline trip is only due to the correlation among unobserved heterogeneity of baseline and different scenarios. To account this, a separate random effect is needed for baseline visit($\mathrm{b_{i0}}$) and scenario-based anticipated future trips($\mathrm{b_{is}}$) and assumed that $\mathrm{b_{i0}}$ and $\mathrm{b_{is}}$ are random outcome from the same distribution, $\mathrm{g}(.)$, which is assumed as normal distribution.

$$\log[\mathrm{E}(\mathrm{Y}_{\mathrm{ij}} | Y_{i0}, x_{\mathrm{ij}}, \mathrm{b}_{\mathrm{i0}}, \mathrm{b}_{\mathrm{is}})] = x_{\mathrm{ij}}^{\mathrm{T}}\beta + \mathrm{b}_{\mathrm{is}} + \alpha \log(\mathrm{y}_{\mathrm{i1}}) + \log(\mathrm{y}_{\mathrm{i1}}) x_{\mathrm{ij}}^{\mathrm{T}}\eta + \mathrm{b}_{\mathrm{i0}} + \mathrm{e}_{\mathrm{ij}} \quad (6)$$

$$(\mathrm{b_i}) \sim \mathrm{g}(.)$$

Using eq. (4) and (5), baseline trip distribution(Y_{i0}) conditional to mean in ZINB framework can be expressed as:

$$\log(\pi_{i0}) = x_{i0}^{T}\gamma_0 + \grave{e}_{i0} \quad (7)$$

$$\log(\mu_{i0}) = x_{i0}^{T}\beta_0 + \sigma_0 b_i + e_{i0} \quad (8)$$

Where β_0 and γ_0 represents parameters and σ_0 represent the standard deviation of the RE parameter b_i estimated for *j* = 0. Aitkin and Alfò (1998), proposed an alternative method for simultaneous estimation of baseline and following epilepsy counts for panels by using specific dummy variables for baseline and following states in a single equation estimation procedure (Solis-Trapala et al., 2007; Fotouhi, 2008; Tsai and Hsiao, 2008). The same approach is used here by defining a dummy d_{ij}, where $d_{ij} = 0$ for baseline and scenario-1, and $d_{ij} = 1$ for scenario-2. By doing this, trip scenario under water quality improvement (scenario-2) can be modeled separately and baseline trips can be added as one of the exogenous variable. In addition to explore the role of baseline dependency in RPSP studies, adding baseline as an exogenous variable would also account the omitted variables that would have affected the recreational demand.

Now eq. (8) will become,

$$\log(\mu_{ij}) = \left[(d_{ij})\left(x_{ij}^{T}\beta_s + \sigma_s b_i + \alpha \log(y_{i0}) + \log(y_{i1})x_{ij}^{T}\right) + (1 - d_{ij})\left(x_{ij}^{T}\beta_b + \sigma bbi+eij \quad (9)\right.\right.$$

$$b_i \sim g(.) \text{ and } \log(\pi_{ij}) = \gamma x_{ij}^{T} + \grave{e}_{ij}$$

where β_s and σ_s represent parameters specific to scenario-2 and β_s and σ_s represent parameters of baseline trip and scenario-1 model. The baseline trip, scenario-1 and scenario-2 models are connected through RE (b_i). However, to address the correlation between baseline dependence and unobserved heterogeneity, different variance parameter for RE in baseline trip, scenario-1 and scenario-2 model are needed.

Thus, (9) would become,

$$\log(\mu_{ij}) = (d_{ij})(x_{ij}^{T}\beta_s + \sigma_s b_{si} + \alpha \log(y_{i0}) + \log(y_{i0})x_{ij}^{T}) + (1 - d_{ij})(x_{ij}^{T}\beta_b + \sigma 0bbi \qquad (10)$$

$$\begin{pmatrix} b_{bi} \\ b_{si} \end{pmatrix} \sim g(.) \text{ and } \log(\pi_{ij}) = \gamma x_{ij}^{T} + \grave{e}_{ij}$$

Following Alfò and Aitkin's (2006), the unobserved heterogeneity among visitors in trip scenario-2 is accounted by b_{si}. However, b_{bi} accounted both dependence between baseline trips and scenario-1, and heterogeneity in the baseline trips. Denoting $b_i = (b_{bi}, b_{si})$ in a panel data set with n_c panels and n_i observations in each panel ***j***, the probability function for a given panel ***j*** can be expressed as the product of the probabilities associated with n_i individual responses (Hur et al., 2002; Rabe-Hesketh et al., 2002),

$$l(y_j|b_i) = \prod_{i=1}^{n_i}[\pi_{ij}I(y_{ij}) + (1 - \pi_{ij})f(y_{ij})] \qquad (11)$$

The marginal probability density is then obtained by integrating over b_i

$$l(.) = \prod_{j=1}^{nc} \int \prod_{i=1}^{n_i r}[\pi_{ij}I(y_{ij}) + (1 - \pi_{ij})f(y_{ij})]g(b_i)\,db_i \qquad (12)$$

As we already assumed that RE are drawn from normal distribution, $g(.)$ represents the standard normal density. The integration over the RE distribution can be approximated numerically using the adaptive Gaussian quadrature and implemented by using PROC

NLMIXED procedure in SAS (Hur et al., 2002; Rabe-Hesketh et al., 2002; Alfò and Aitkin, 2006).

3.2.1 Data and model

The data used for this study were collected from 5 counties in and around the Upper Big Walnut Creek (UBWC) watershed, OH through a mail survey after the 2008 recreational season (copy of the survey instrument is attached in Appendix B). As boaters and anglers are avid users of the water-based recreation in UBWC, survey was restricted to registered boaters and licensed anglers who are residents of these counties. Names and addresses of the registered boaters and licensed anglers were collected from the Ohio Department of Natural Resource (ODNR). A separate questionnaire was mailed to randomly selected 700 boaters and 700 anglers from the ODNR database. To avoid reaching both the surveys at the same home, registered boaters were removed from the anglers list wherever same name and address were found. The total samples are proportionately distributed over the counties based on the total number of registered boaters and anglers in each county. The first set of survey was sent after the 2008 recreational season and a follow-up questionnaire was sent two weeks after the first mailing. Additionally, a reminder post card was sent after four weeks to increase participation in the survey. The overall response rate for the survey was 29%, after accounting for the undelivered questionnaire. Some of the surveys were discarded due to lack of much information. Additionally, respondent who stated that they would take more number of trips with more information about current water quality and those reported lower number of trips with improved water quality (Huang et al., 1997).

The survey gathered a wide range of information from the visitors, which included the number of times they had visited different zones of UBWC watershed during 2008. Additionally, information about the mode of travel used by the visitors to reach the site and other demographic characteristics were also collected. Moreover, the questionnaire for anglers and boaters had activity-specific questions for angling and boating, respectively. Given that boaters are likely to fish and anglers are likely to use boats, boaters were asked about their fishing behavior, and anglers were asked whether or not they used boats.

As the goal of this study was to measure the recreational value of water quality from the current level of water quality impairments to the desired level as per the EPA standards, two scenario based questions were also included in the survey. Maps of the watershed were included in the questionnaire in four places to provide spatial location of the visit as well as water quality information. The first map of the watershed, which was given on the front page of the questionnaire, gives details of the neighboring counties and nearby towns so that respondent can locate their star and end point of recreational visit to the watershed. The UBWC watershed was divided into 4 zones in other three maps for an easy understanding of site-specific current and future water quality improvements. The second map was used to collect the information on zone-specific visits by the respondents during 2008 recreational season. Zone-specific information about current water quality impairments was provided in the third map with an intention of helping the respondents to answer the question “how many trips they would have taken in 2008, if they had information about water quality impairments in the watershed”. In the fourth map, zonewise water quality improvements were reported to mimic the hypothetical water quality improvement scenario and then asked the respondents to state how many additional trips they would have taken to each zone under improved water quality conditions.

For the analysis, only the single day trips taken within the UBWC were considered. The dependent and explanatory variables of the empirical models were constructed on the basis of previous research (Whitehead et al., 1998; Bhatt, 2003; Meisner et al., 2006, Sommer and Sohngen, 2007), which showed that the visitor's recreational preference is related to visitor's characteristics, travel distance, and environmental quality of travel sites.

The travel cost (TC) was defined as round trip transportation cost to the site from visitor's house plus opportunity costs of time. In baseline trip, zone-1 was the most preferred recreational site for both anglers and boaters. So for baseline trips, round trip transportation cost to zone-1 was used. However, for the two water quality improvement scenarios, visitors showed diverse site choices. Thus, weighted average of travel price with number of trips to the zone was considered as the transportation cost. But for all zero trips in baseline and two water quality scenarios, transportation cost to zone-1 was used. Additionally, reported travel distance was checked with map-quest and found that both were closely matched. Hourly opportunity costs of time was estimated as 30% of the value of the individual's wages (Cesario, 1976), where hourly wages are total income divided by 2000 working hours per year. Additionally, household income (I), expressed in $10,000 was also considered as an explanatory variable. The average reported household income, $65000 was slightly higher than the census reported values for the region, which is also reported by other recreational studies from the region (Hushak., 1999; Sommer and Sohngen, 2007).

Variables	Mean	Min	Max	STD	Definition of variables
Dependent Variable					
Trips	2.55	0	80	11.6	Number of one day trips in an year
Independent Variables					
I	6.71	0.5	9.5	2.58	Income in 10000 dollars
TC	14.1	0.4	28	6.51	Travel cost in dollars
FD	0.39	0	1	0.49	Fish dummy variable: 1 = angling and 0 = boating
P2D	0.33	0	1	0.47	Fixed effect dummy for stated preference-1
P2I	2.46	0	9.5	3.01	Interaction dummy for P2D and Income
P2TC	4.70	0	28	7.64	Interaction dummy for P2D and Travel cost
P2FD	0.13	0	1	0.33	Interaction dummy for P2D and fish dummy
WQ	0.80	0	1	0.40	Water quality perception: 1= important or higher, 0= otherwise
Base	2.36	0	38	5.27	Number of baseline trip taken by visitor

Table 3.1 Definition and descriptive statistics of variables used in trip demand estimation.

Angling and boating were the two primary recreational activities, therefore a dummy variable was introduced to capture the influence of primary recreational activity on recreational decision. Thus, a fish dummy variable (FD), with a value of 1 if the primary activity is angling, and 0 otherwise was added. As scenario-1 trip was modeled along with the baseline trip, an intercept dummy for trip scenario-1 (P2D) was added. The P2D is 1 for trip scenario-1and 0 otherwise. The interaction of P2D with TC, I and FD were also added as explanatory variables to capture the changes in slope of demand curve with trip scenario-1. So, the specified model was able to address the differences in the slope of the demand curve between scenario-1 and baseline trip. An additional dummy variable was also added for capturing the water quality perception (WQ) of respondents. The dummy is 1 if the WQ of the respondent is important or very important, and 0 otherwise. The descriptive statistics of explanatory variables are given in Table 3.1. After a series of stepwise run with the above mentioned explanatory variables, the final ZINB model is defined as follows:

Logit trip participation model:

$$\log(\pi_{ij}) = \gamma_0 + \gamma_1 * I + \gamma_2 * TC + \gamma_3 * FD + \grave{e}_{ij}$$

Mean trip model(λ_i):

$$\log(\mu_{ij}) = (d_{ij})*(\beta_0 + \beta_1 * I + \beta_2 * TC + \beta_3 * FD + \beta_4 * BaseTrip + \sigma_s b_{si}) + (1 - d_{ij})*(\beta_5 + \beta_6 * I + \beta_7 * TC + \beta_8 * FD + \beta_9 * P2D + \beta_{10} * P2I + \beta_{11} * P2TC + \sigma_0 b_{0i}) + e_{ij}$$

$$\begin{pmatrix} b_{0i} \\ b_{si} \end{pmatrix} \sim g(.)$$

Where β_0 to β_4 represents coefficients of trip demand model for scenario-2 and β_5 to β_{11} represents coefficients of trip demand for baseline and scenario-1 combined. The mean trip model has two parts, scenario-2-model, and baseline and scenario-1 model. The mean trip model consists of recreational demand parameters for baseline demand, and intercept and slope dummy variables for scenario-1.

3.2.2 Consumer surplus estimation

The above demand model also allows estimating changes in the consumer surplus baseline trip, scenario-1 and scenario-2. As TC is equivalent of a price variable in a standard demand equation, the per person consumer surplus under a given quality level can be calculated as follows (Bockstael and Strand, 1987) for a ZINB function,

$$\text{Consumer Surplus (CS)} = -(1-\pi)\frac{e^{\bar{x}\beta}}{\beta_{TC}}$$

where β_{TC} is the estimated parameter of TC. In the case of the ZINB model, expected consumer surplus must be weighted by (1 - π), where π is a function of variables that affect the participation decision. The additional welfare generated with water quality improvements could be measured by the following equation (Whitehead et al., 1998),

$$\Delta\text{CS} = \left[(1-\pi)\frac{e^{\bar{x}\beta_1}}{\beta_{TC}^{1}}\right] - \left[(1-\pi)\frac{e^{\bar{x}\beta_0}}{\beta_{TC}^{0}}\right]$$

where β_1 and β_0 are coefficients for anticipated trip demand model and baseline trip demand model.

3.3 Results

A consistency in underlying structural preference means that the parameters of the scenarios are not significantly different from zero. The estimated recreational demand showed that only the dummy for scenario-1 is significantly different from zero at 0.05 level and all other coefficients of scenario-1 dummy interactions were not significant (Model-1 in Table 3.2). This means that under scenario-1, demand curve would shift downward. A joint testing of all coefficients associated with scenario-1, dummy and interaction (P2D, P2I, P2TC and P2FD) were applied to know the parameters under scenario-1 jointly equal to zero. The results revealed that the coefficients are significantly different from zero (χ^2 = 18.72[4 df]). Thus, RP and SP of scenario-1 represent different recreational demand models. However, a joint test for coefficients of interaction of scenario-1 dummy was attempted in next step, which indicated that the elasticity coefficients of interaction of dummy are not significantly different from the revealed behavior data elasticity coefficients (χ^2 = 7.34[3 df]).

	Model-1		Model-2	
	β	SE	β	SE
Baseline and Scenario-1				
Constant	1.050***	0.254	1.054***	0.254
TC	-0.025***	-0.013	-0.026***	-0.012
I	0.022	0.019	0.021	0.019
FD	0.078	0.121	0.080	0.121
P2D	-0.91**	0.494	-0.93**	0.508
P2TC	-0.014	0.022		
P2I	0.010	0.009		
P2FD	-0.012	0.007		
Scenario-2				
Constant	1.32***	0.315	1.100***	0.327
TC	-0.027**	0.012	-0.025**	-0.011
I	0.025	0.018	0.023	-0.017
FD	-0.186	0.339	0.214	-0.226
Base-dependent	0.017**	0.008	0.015**	0.006
κ	1.651***	0.136	1.524***	0.151
σ_b^2	2.079***	0.214	2.030***	0.125
σ_s^2	1.041***	0.091	1.013***	0.101
ρ	1.142***	0.147	0.742***	0.059
Trip Participation				
Constant	-0.945***	0.349	-0.953***	0.361
TC	-0.048	0.061	-0.050	0.071
I	0.043	0.045	0.043	0.062
FD	0.540***	0.192	0.590***	0.204
-2LL	2415.2		2418.6	

**** and *** 5% and 1% level of significance respectively.**

Table 3.2 Baseline dependent trip demand model.

In the next step, the model is estimated by dropping dummy interaction variables of scenario-1 (Model-2 in Table 3.2). However, the coefficients of the new model (model-2) did not differ much from model-1. Additionally, dummy for scenario-1 was again significant under model-2, which revealed the downward shift in demand with more information about pollution. Furthermore, two more joint tests were performed to know the equality of coefficients of demand shift under scenario-1 and scenario-2, and equality of slope changing factors under scenario-2. The test for equality of demand shifting coefficients revealed that demand shift coefficients of scenario-1 and scenario-2 were significantly different ($\chi^2 = 2.91[1\ df]$) and slope coefficients of scenario-2 was also significantly different ($\chi^2 = 6.27[3\ df]$). The coefficients of variables in the constraint model and original model did not change after dropping slope changing variables in scenario-1. Therefore it is concluded that SP and RP data can be combined by using constraint model. The upward (in scenario-2) and downward (in scenario-1) shift of demand curve observed with increase and decrease in water quality, respectively, was in accordance with the expected economic behavior. Thus, model-2 is used for understanding the recreational behavior with water quality changes and subsequent consumer surplus calculation associated with the water quality changes.

The signs of the trip demand models were in line with demand theory. In the case of baseline trip demand, only TC is significant at 0.01 level with negative sign. Additionally, the negative sign of the dummy for scenario-1 indicates that demand would shift down if visitors had information about water quality while they decided about the trip. In the case of trip scenario-2, TC was significant along with the baseline trips. This shows that baseline trip is a deciding factor in future trip decisions. The intercept of the trip scenario-2 was higher than the baseline trip demand model, which indicates the outward shift of demand function due to water quality improvements. Additionally, price elasticity was lesser than baseline trip demand model. Moreover, positive value of coefficient of income under trip scenario-2 was in line with theory, but it was not significant.

Parameter estimates of the participation model revealed that only dummy variable for angling is significant. As the sign of the logit participation model represents the non-participant action by the visitor, the sign should be changed to the opposite while interpreting for participation by a respondent. Thus, the negative sign of the TC coefficient is not expected and the reasons as to why this is so are not easily explained. However, coefficient of TC is not significant in the model.

The parameters for the RE components associated with the anticipated trip model, and covariance of anticipated and baseline trip models were significant. This denotes that correlated heterogeneity exists among respondents, which were correlated across anticipated trip and baseline trip.

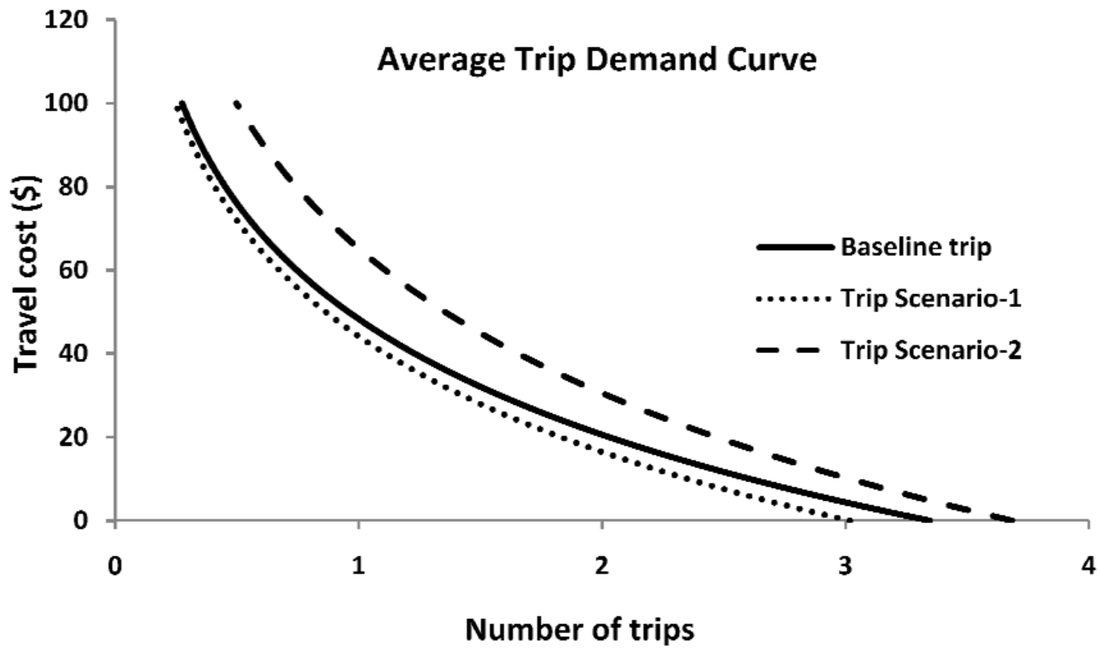

Fig. 3.1 Average trip demand curve.

The predicted average trip demand curve for the baseline trip and the trip-scenario 1 and 2 are given in Fig.3.1. It is clear that with improvements in water quality (scenario-2), the trip demand curve shifted away from the demand curve of baseline trip. However, given more information about current water quality impairment in the watershed (scenario-1), trip demand curve shifted inwardly compared to that of the baseline trip. It could be inferred that as more information about water quality impairments are available to the visitors, there would be a chance for the reduction in trips taken by anglers and boaters. In other words, if the authority delays action for improving the water quality in UBWC, recreational value of the site would eventually decline. Interestingly, under higher water quality setting in scenario-2, the price elasticity of demand for recreation would be more inelastic compared to the baseline trip demand.

Baseline and Scenario-1 Trip Demand		
Variable	Coefficients	Elasticity
TC	-0.026	-2.57
I	0.021	2.122
FD	0.080	8.328
P2D	-0.310	-60.541
Scenario-2 Trip Demand		
TC	-0.025	-2.469
I	0.023	2.326
FD	0.214	23.862
Participation Model		
TC	-0.050	-4.88
I	0.043	4.390
FD	0.590	80.40

Table 3.3 Sensitivity of parameters.

The predictors in ZINB model were multiplicative because of its exponential framework. Thus, the coefficients of the model could be interpreted as the percentage change in the expected trips by transforming regression coefficients to $100 * [e^{\beta * \delta} - 1]$, where β is the coefficient of parameter and δ is the unit change in the coefficient (Atkins and Gallop, 2007; Meisner and Wang, 2006). Based on this, the sensitivity of estimated ZINB model with changes in the parameter values is given in Table 3.3. A unitary increase in TC would likely to reduce anticipated trips by 2.57 % in baseline-trip demand and 2.47 % in scenario-2 and more information about water quality would decrease the trip by about 60 %.

The results of model-2 were used to estimate the average per trip consumer surplus under baseline and two scenarios. The predicted number of trips was also calculated to derive the annual consumer surplus generated by an average visitor. For the baseline trip, average annual consumer surplus for a visitor (boater and angler) was $22.21 per trip and predicted number of trips per year was 2.35 (Table 3.4). Thus, annual consumer surplus generated was $52.23 by taking trips to the UBWC. However, under trip scenario-1, consumer surplus per trip and predicted number of trips per year were reduced to $16.29 and 1.72 respectively. So, the annual consumer surplus of a trip to the watershed was also reduced to $28.09. As water pollution is economically bad, it is rational that consumer would reduce number of trips to the site when they have enough information about the pollution level in the watershed. On the other hand, under water quality improvement scenario, the trip demand curve shifted outward from the baseline demand curve, resulted in an increase in number of trips to 2.78 along with a higher consumer surplus for an average visitor, $32.79 and annual consumer surplus generated per trip by $91.11. For the anglers, the consumer surplus in the baseline trip was $22.21 per trip and the average number of trips to the site was 2.47. Thus, the total annual surplus generated over year would be $54.86, while that corresponding to boaters would be $50.64. Under trip scenario-1, the average of annual consumer surplus for boaters and anglers is reduced to $16.29 per trip, and the anglers make about 1.81 trips per year, which resulted in the decrease in annual consumer surplus of \$29.51. For trip scenario-1, number of trips by anglers and boaters were less than the baseline trips. However, for trip scenario-2, the number of trips by anglers and boaters were increased significantly to 2.81 and 2.76 respectively. Because anglers take more trips, they also gain the most from water quality improvements. Annual consumer surplus for anglers increased from \$54.86 per year in the baseline trip to \$92.24 per year in the trip scenario-2. The potential aggregate benefit generated from water quality improvement was calculated using estimated annual average consumer surplus for the trip. As approximately 40 % of the respondents of the survey visited the site during 2008 recreational season, it is assumed that 40 % of the total registered boaters and anglers (97,000) would participate in recreational activity annually in the watershed. Baseline consumer surplus from recreational boating and angling trips to the UBWC was 2.03 million. If current water quality issues are not addressed properly, the annual consumer surplus would drop down to 1.09 million, indicating that the annual welfare loss due to pollution is 0.94 million. However, an improvement in water quality could generate a welfare gain of 3.53 million.

	Baseline	Trip Scenario-1	Trip Scenario-2
Consumer Surplus (CS)			
CS per trip ($$ per trip)	22.21	16.29	32.79
Δ CS- Baseline		-5.92	16.50
Δ CS- Scenario-1	-5.92		10.59
Predicted Number of Trips			
All	2.35	1.72	2.78
Angler	2.47	1.81	2.81
Boater	2.28	1.67	2.76
Annual Consumer Surplus ($ per year)			
All	52.23	28.09	91.11
Angler	54.86	29.51	92.24
Boater	50.64	27.24	90.41

Table 3.4 Estimated consumer surplus for baseline, scenario-1 and scenario-2.

3.4 Summary and conclusions

The primary focus of the paper was to accommodate baseline dependence and unobserved heterogeneity in continuous choice recreational demand model with revealed preference-stated preference framework. The estimated model explicitly used the number of visits to a recreational site during a baseline period as a predictive variable for anticipated future recreational demand under improved water quality. Additionally, unobserved heterogeneity and correlation between unobserved heterogeneity in baseline trip model and scenario-2 model were also explored. The results clearly showed that baseline experience is a significant determining factor for future visitation decisions. Additionally, the high significance of the unobserved heterogeneity parameter and their correlation parameters indicated that in studies with revealed preference-stated preference framework, correlation between heterogeneity is also an important factor. This study estimated the value of water quality improvements in Upper Big Walnut Creek Watershed, Central Ohio. Our methods combined the revealed and stated preference techniques to estimate a panel data model that captures the welfare effects of changes across two scenarios of water quality improvements. The data were derived from a survey of 1400 boaters and anglers after 2008 recreational season. A total of 193 responses were obtained, of which 190 were usable for the estimates presented in this paper. When incorrect addresses were removed from the total sample, the effective response rate was 23 %. A comparison of the respondents in our survey with U.S. Census data indicated that our respondents have slightly higher income than the population in the region, in general. The respondents were asked to provide 2008 recreational activity in the watershed, including number of trips, specific site for the trips, number of people in the trips, the kind of activity performed during the trips, cost of the trips and the role of water quality in trip decision making. Survey results revealed that anglers and boaters take 1.3 single day trips per year within the Upper Big Walnut Creek Watershed under baseline water quality conditions. The stated preference questions in the questionnaire provided individuals with more information about current water quality data. The respondents were asked to provide their trip taking behavior in 2008 recreational season, if this water quality information were available. Additionally, a water quality improvement scenario, trip scenario-2 (all the water bodies in the watershed meets EPA standard) was presented and asked the respondents about their probable additional trips to the watershed under improved water quality conditions. The trip demand curve under scenario-1 was shifted down from the baseline trip demand curve, resulted in significant reduction in number of trips and consumer surplus. However, trip scenario-2 resulted in a shift of demand curve further away from the baseline curve, which leads to more trips by both anglers and boaters and considerable increase in consumer surplus.

A baseline trip dependent model was applied to estimate trip demand parameters of the baseline, trip scenario-1 and trip scenario-2 simultaneously. Additionally, the model was also able to address the unobserved heterogeneity and baseline dependence in trip demand estimation. The baseline trips were significant in estimated trip demand function for trip scenario-1 and trip-scenario-2. From the analysis, it was clear that the scenario-1 is an inferior good for the society, indicating that, as income of people increases, the number of trips to the site decreases. On the contrary, baseline trip and trip under water quality improvement (scenario-2) were normal good. Additionally, trip demand curve for water quality improvements was steep compared to that for the baseline trip, which suggest that price elasticity demand for improved water quality was less elastic than that of baseline trip. The estimated annual aggregated benefit was 2.03 million. But, if the current information about water quality impairments were available to the visitor when they make their trip plans, aggregate surplus would reduce to 1.09 million. However, water quality improvement would make significant increase in benefit to 3.53 million.

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CHAPTER 4

ESSAY 3

INTEGRATED WATERSHED ECONOMIC MODEL FOR NON-POINT SOURCE POLLUTION MANAGEMENT IN UPPER BIG WALNUT CREEK WATERSHED, OH.

4.1 Introduction

Today, non-point source pollution (NPS) is one of the major sources of water quality impairments globally (UNEP, 2007). In the US, nutrient pollution is the leading cause of water quality issues in lakes and estuaries (USEPA, 2002). The maximum concentration of nutrients in streams is found to be in agricultural basins, and it is correlated with nutrient inputs from fertilizers and manures. This clearly shows the role of agricultural practices in water quality degradation (USGS, 1999). To improve the quality of water bodies, the United States Environmental Protection Agency (USEPA) mandates individual states to implement the Total Maximum Daily Load (TDML) (USEPA, 2002). The state and federal governments are working with several conservation programs to reduce the NPS load from agriculture (Mausbach and Dedrick, 2004).

At a watershed scale, two strategies can offer potential solutions to the problem of migration of nutrients from agricultural fields to water resources. The first strategy is to change the on-farm management practices to ensure reduction in nutrient application, thereby reducing nutrient loads from the farm. To achieve this, there should be a shift in crops that demand lower nutrient inputs or adoption of efficient nutrient/irrigation/drainage management practices that could reduce nutrient load from the farm. In nutshell, this strategy involves farmer's optimal decisions about land allocation, and crop and technology selections. The second strategy is to siphon-out the nutrients from the drainage system or from the runoff coming out of agricultural farm before it reaches the water resources. This is accomplished by creating vegetative or riparian buffers, or wetlands to filter out the pollutants from the stream flow or by using specially designed ditches that facilitates nutrient assimilation. Thus, policy makers can propose appropriate policies that would result a shift in land allocation, and/or crop and technology selection for reducing nutrient load from farm, or they can introduce programs that would remove the pollutants before reaching the water bodies. The technical and economical aspects of using these two broad approaches for reducing the nutrient transport from agricultural field have resulted in a rich stream of research (Nakoa and Sohngen, 2000; Mitsch et al., 1999; Heimlich et al., 1998) in this field.

However, the ever-increasing water quality impairment by agricultural NPS in US clearly shows that the task of formulating and implementing the cost-effective policies for controlling the NPS impact on water resources is challenging. This clearly reflects the complexity of the NPS generation and transport on a landscape. On the one side, NPS is generated and transported on a highly heterogeneous biophysical realm with tremendous spatial and temporal variability, and on the other side, varied human activities, especially farm practices across the landscape, have a major role in the magnitude of NPS load from a landscape (Naevdal, 2001; Carpenter et al., 1999; Ribaudo et al. 1999). Thus, it is not easy to derive *cause-effect* relationship between human activity and NPS load using a single disciplinary framework when the NPS process is compounded by both human and biophysical realities (SAB, 2008; Elofsson, 2003). Therefore, the NPS management and policy analysis must be addressed through a multidisciplinary methodology, a methodology that could not only capture the dynamic processes and uncertainties of nutrient movements in agro-ecosystems, starting from nutrient application, intake by plants, transport from the field to downstream water reservoir with possible nutrient assimilation in-between, but also integrate the farmer's profit function by internalizing the social cost associated with the pollution.

An integrated watershed-economic modeling (IWEM) offers such a holistic approach, where compounding effect of biophysical and anthropogenic variables can be identified and their impact on NPS generation and transport can be partitioned. This is achieved by using a watershed scale modeling of NPS movement along with separate economic behavioral model to deal with socio-economic aspects of NPS loading (SAB, 2008). This essay presents an integration of possible agricultural best management practices (BMP) for NPS reduction generated by the SWAT-based watershed model described in the first essay with the estimates generated in the second essay in relation to the economic value of water quality improvement in the Upper Big Walnut Creek

(UBWC) watershed of central Ohio. SAB report noted that generally in NPS management studies did not consider the multiple benefits generated by NPS reduction (SAB, 2008). However, this study integrated economic and watershed modeling approaches for a comprehensive assessment of the costs and benefits, including co-benefits, of various management options. The IWEM is applied to the UBWC watershed of Ohio, which was identified by Ohio EPA as an impaired watershed due to nutrient enrichment from current agricultural management practices (Ohio EPA, 2005).

The section 2 briefly describes the methodological approach used in the paper, specifically for the derivation of the costs and benefits of water quality improvement, generation of the possible BMPs for the watershed using the already developed watershed model and finally the integration of the two sub-models. The next section deals with the results and discussion, and the final section describes some concluding thoughts.

4.2 Methodology

This section presents a simple conceptual model for agricultural NPS management in dynamic programming (DP) framework to illustrate the usefulness of dynamic programming as a tool for integrating the watershed model with the economic model for managing NPS.

The model links the nitrogen (N) export from an upstream agricultural farm to the downstream water reservoir through a channel. The nutrient transport from the agricultural farm results in pollution stock build up in the downstream water reservoir, which leads to ecosystem damages. Additionally, it is assumed that the marginal damage of NPS is a continuous function of pollution stock. This model addresses nutrient assimilation at two levels: (i) assimilation within the channel that connects the farm and the downstream water reservoir, and (ii) assimilation at the downstream water reservoir. The important elements of the dynamic programming model are given below with a detailed description of the procedures followed.

Let $\Re(n_t)$ be the revenue from the farm, $C(n_t)$ be the fertilizer cost and $V(y)$ be the unit cost of other inputs for the corn production per hectare. Let $D(N_w)$ be the environmental damage cost associated with N content (N_w) in the downstream water reservoir and r be the discount factor, which has the value between 0 and 1. A deterministic dynamic program can be defined with an objective function that maximizes discounted net social benefits (1) with a transition function (2), which can be written as,

$$\underset{N}{Max} U = \sum_{t=0}^{t=T} \frac{1}{(1+r)^t} \left(\Re(n_t) - \left[C(n_t) + V(y) + D(N_{wt}) \right] \right) \tag{1}$$

$$N_{wt} = f(n_t) \tag{2}$$

(1) and (2) represents reward function and state transition function of dynamic programming, respectively, which is profit from farming with internalized cost of nutrient pollution and soil N balance in the present study. Assume that the nitrate stock at the watershed is N_t, which forms one state variable in the model. In each crop season, an n_t amount of N is applied to the field for increasing the crop yield. So the total N available to the plant is a cumulative of $N_t + n_t$. Of which, a fraction of the available N is absorbed by the plant for its biological needs (γ). In addition, another fraction (λ) is flushed out from the field through drainage and runoff water. So, λ can be considered as N flushing coefficient of the watershed. The rest of the applied N (ΔN_t) is added to the

initial N stock N_t . So N stock balance in a year 't' at the watershed is N_{t+1}, which is the first state variable and can be expressed as,

$$N_{t+1} = N_t + \Delta N_t \tag{3}$$

$$N_{t+1} = N_t + n_t - \gamma\left[N_t + n_t\right] - \lambda\left[N_t + n_t\right] \tag{4}$$

In each year $\lambda\left[N_t + n_t\right]$ amount of N is flushed out from the watershed. The on-farm technology options to reduce nutrient loading needs to be addressed through n_t, γ and λ. This means that the soil N balance varies with the total quantity of N application and the time (single or multiple split application) of application. Additionally, the crop choice and crop rotation (with/without a cover crop) would affect the crop uptake factor (γ). The presence of buffers on the edge of the farm would reduce the value of λ.

Generally the flushed out water from the field is carried to the downstream water reservoir by a common drainage channel (Hall and Tank, 2003; Peterson et al., 2001; Alexander et al., 2000; Seitzinger et al., 2002). So N_{st} can be expressed as,

$$N_{st} = (\lambda[N_t + n_t]) \times (1 - \phi) \tag{5}$$

where, ϕ is the assimilation coefficient in the stream. Suppose the downstream water body initially had a N concentration of N_{wt}. In which, a portion $\varphi\ N_{wt}$ undergoes natural assimilation, where φ is the rate of assimilation coefficient. Now we can transition the function for N concentration in the downstream water reservoir, which is the second state variable in the dynamic program. This can be written as,

$$N_{wt+1} = \left(N_{st} + N_{wt}\right) * \left(1 - \varphi\right) \tag{6}$$

The watershed model developed in Essay-1 was used for deriving the technology specific parameters, crop production functions and nutrient loading functions for the watershed. The benefit measures estimated from Essay-2 along with other benefit estimates of water quality improvement in UBWC watershed and cost estimates of the technology options were used to specify the dynamic programming model.

4.2.1 Simulation of conservation management scenarios

The following section describes the conservation management options simulated using the SWAT model for deriving crop and technology specific production functions and N loading function (A comprehensive description of SWAT modeling was reported in Essay-1). The simulations of BMP were completed in several steps. Separate management files were created for each of the BMP technologies listed below.

Step-1 Selection of crops and cropping systems for simulations

As corn, soybean and wheat are the predominant crops cultivated in the UBWC, these crops were considered in different rotations for reducing the nutrient load from the farm. The specific rotations selected were: corn-corn (C-C), corn-soybean (C-S) and corn-soybean-wheat (C-S-W). For each of these crop rotations, 16 years of baseline management files were extended to 25 years.

Step-2 Selection of fertilizer application strategies

The three crop rotations were separately analyzed for split application of N fertilizer, ${}^{2}/{}_{3}^{rd}$ of total N fertilizer applied at planting and ${}^{1}/{}_{3}^{rd}$ one month after planting as side dressed (Witter, 2006).

Step-3 Simulation of tillage strategy

Conservation tillage was selected as a promising conservation method for the UBWC. Thus selected crop rotations were separately analyzed for the impact of conservation tillage adoption for reduction in nutrient loading.

Step-4 Simulation of cover crop strategy

It is reported that cover cropping with existing cropping system would reduce the quantity of nutrient transport from the farm (Staver and Brinsfield, 1998). As rye (*Secale cereale* L.) has been used successfully as a cover crop, it was introduced in each of the selected cropping rotations for the simulation exercise.

Step-5 Simulation of vegetative buffer

A 10 m vegetative buffer is also included in the BMP list as a nutrient load reduction strategy (Lovell and Sullivan, 2006; Witter 2006). As the exact area under buffer in each land unit was not readily available in the SWAT output, buffer area was calculated from the hydrologic response unit (HRU) map of UBWC with 10 m buffer, derived by Arc-GIS. Thus, the aggregated watershed area lost from agricultural production was derived.

Simulations of each of the crop rotation-technology combinations were performed separately. The existence of same kind of crop rotation-technology combination in baseline was accounted for while deriving watershed scale production and loading functions. To capture the adoption of area under each technology-crop rotation combination, 7 runs were made with different levels of adoption (% area under each technology) of technology in each of the sub-watersheds. During each run, scenarios were simulated for 25 years from 2010 using climatic inputs for UBWC created by weather generator in the SWAT. The average annual outputs for the watershed were derived.

4.2.2 Baseline crop production function (BPF)

The baseline N production function for corn and wheat, and phosphorus (P) production function for soybean were estimated by using SWAT model for the UBWC watershed. The SWAT derived crop yields were generated by running the SWAT with varied levels of N application for corn and wheat, and P for soybean for the watershed. A quadratic relationship between applied nutrients and the yield were established by regressing applied nutrient against simulated yields of for different crops for the watershed.

$$BPF_i = a_i + b_i \times x_i - c_i \times {x_i}^2 \qquad (7)$$

i= crop and x = nutrients applied for crop production, N fertilizer for corn and wheat, and P for soybean. Now the per hectare profit (π_{ih}) can be written as,

$$\pi_i \quad = [(a_i + b_i \times x_i - c_i \times {x_i}^2) \times P_i]\text{- } P_x \times \ x_i\text{-}V_i(Y_i) \qquad (8)$$

P_{yi} , P_x and $V_i(Y_i)$ are unit price of crop output, nutrient input and cost of other variable inputs, respectively.

4.2.3 Baseline soil nitrogen stock

The baseline soil N balance (N_t) equation was derived for the watershed by the SWAT model. The soil-N balance equation consists of N applied for crop production

(n_t), N carried over from last year (N_{t-1}), fraction of N uptake by crop (α) and the fraction of the soil-N flushed-out from the watershed (γ), which can be written as,

$$N_t = (N_{t-1} + n_t) - \alpha \quad (N_{t-1} + n_t) - \gamma \quad (N_{t-1} + n_t) \tag{9}$$

So the baseline N load can be represented as,

$$\text{N Load}_t = \gamma \quad (N_{t-1} + n_t) \tag{10}$$

However, in the case of soil-N balance for soybean, N fixation component (N-Fix) also has to be included. As the level of N fixation depends on total biomass production. N-Fix is introduced in soil-N balance equation as,

$$\text{NFix} \quad = \text{Min}[\varphi \quad * \text{Y} \quad , 80] \tag{11}$$

φ is watershed specific N fixation factor, which is derived by dividing average N fixed by soybean with average soybean yield (Y) from SWAT model results. However, the average N fixed was capped at 80 kg/ha, which is the average N fixation rate from soybean reported for the state of Ohio (Russelle Birr, 2004). Thus, Soil-N balance for soybean is,

$$N_t = (N_{t-1} + n_t + \text{NFix}_t) - \gamma \quad (N_{t-1} + \text{NFix}_t) \tag{12}$$

$$\text{N Load}_i = \gamma \quad (N_{it-1} + \text{NFix}_t) \tag{13}$$

Generally, BMP technologies are applied simultaneously by a farmer. Thus three different technology sets were generated for scenario analysis in DP with current crops cultivated in the UBWC watershed (45% corn, 45% soybean and 10% wheat).

- Technology Set-1: The current level of agricultural production and N loading
- Technology set-2: Cover crop, vegetative buffer and conservation tillage

- Technology set-3: Technology set-2 and split-N fertilizer application

4.2.4 Change in baseline production and soil-N balance with level of technology adoption

The watershed scale production and soil-N balance for each crop-rotation and technology combinations was calculated. It was expressed as an exponential function of baseline yield and % area of technology adoption.

$$PF_{hij} = BPF_{hij}e^{\beta h_{ij}*100} \qquad (14)$$

Where $h, i,\ j$ and k represents crop rotation, crop in each of the crop rotation and technology and technology set, respectively. To translate the problem into a simple DP framework, the present study assumed full adoption of technology. Thus, β_{hij} was multiplied by 100 in the production function. However, changes in crop production due to simultaneous adoption of BMP's technologies (Technology set-2 and Technology Set-3), average yield deviation from the baseline for Technology set-2 and Technology Set-3 were used. Thus,

$$APF_{hij} = \left[\left(BPF_i \times average\left(e^{\beta_{hij}\times 100}\right)\right)\right] \qquad (15)$$

In a similar way, the N loading rate with different conservation technologies was also adjusted.

$$N\_\mathrm{load}_{h,ij} = N\_Load_{hij}e^{\theta_{hij}*100} \qquad (16)$$

Where β, and θ are parameters that represent changes in crop yield and N load from baseline due to full adoption of technology. As separate simulations were made for each crop-rotation technology combination, it is assumed that simultaneous application of the conservation technologies would result in a multiplier impact on pollution load reduction and other nutrient processes in the soil. Thus, for a given crop rotation (h=1), the nutrient loading from different BMP technologies can be expressed,

$$N\_\text{load}_{1ij} = N\_Load_{1ij} \prod_j e^{\theta_{1ij} \times 100} \tag{17}$$

and

$$AN\_\text{load}_{ij} = \left[\left(N_{\text{load}_i} \prod_j e^{\theta_{ij} \times (1-A_{buffer}) \times 100}\right) \times {e_b}^{\hat{\theta}_{ij} * 100}\right] \tag{18}$$

In the case of buffer, 100 % of adoption means that all the HRU's in UBWC watershed adopted with 10 meter buffer filters and ${e_b}^{\hat{\theta}_{ij} * 100}$ is the pollution reduction by using buffer.

4.2.5 Change in cost with level of technology adoption

The cost function consists of variable cost of applied N and variable cost of other inputs expressed as function of yield, social cost of pollution load and technology cost of conservation practices. The applied N would not change across the conservation technologies except for N reduction options. Additional cost involved in adoption of conservation technologies would be applicable to split-N application, cover cropping and maintenance of buffer strip. In the case of split-N application, the additional application cost is calculated as $25 per hectare (Hoorman, 2009). However, in the case of cover cropping, cost of seed, sowing and killing of the crop have to be accounted, that is estimated as $110 per hectare (Hoorman, 2009). The vegetative buffer cost was calculated based on Sohngen 2003.

4.2.6 The social damage cost of nitrogen loading

The benefits that are offered to the society from water resources are multitude. It is interesting to note that the worth of the services from a water resource is really the quality of the water resource valued by the society. Thus, water quality impairment will impute an opportunity cost on the society. This can be termed as a social damage cost (SDC) of water pollution. The SDC is actually the economic value of opportunities that a society lost due to the decline in water quality. Therefore, we can establish a direct relationship between the amount of pollution and SDC through a social damage function. In our social damage function, marginal damages are considered as a continuous function of pollution stock.

Since a functional form of the social damage function is not readily available, a possible option is to make an approximation based on theory. An important piece of information needed to make an approximation for a function is to obtain information about the shapes of the social damage function. Therefore it is important to find out what could be the probable shape of social damage function with pollution levels. As a starting point, we set a zero level of N loading. It is clear that at a zero level of N loading, SDC will be zero. The next logical step is to determine the upper boundary of N loading with SDC still zero.

It was stated earlier that an ecosystem has an innate capacity to assimilate some portion of N load, resulting a reduction in pollution load to the downstream water reservoir at two levels, one is in the channel connecting the farm and the water reservoir (δ) and the other is in the downstream water body (φ).

Logically zero SDC can be extended up, until the assimilation potential of an ecosystem is not reached. Once the natural assimilation is used, the SDC curve will go up with the N load from the farm. Beyond this point, with more N export to a fixed volume of water in a reservoir, the proportion of N in the water will increase. In this situation, two things have to be considered.

- A higher level of pollution will also increase the probability of exposure for the different players in an ecosystem to the polluted environment. For example, as N loading goes up, there is a greater probability that the dependent population would be exposed to poor quality water
- At higher concentration levels of N, the magnitude of the damage caused by the pollutant will also increase (this holds true for vehicular pollution or any other form of air pollution as well).

These SDC will increase more-than-proportionately with an incremental N load to water reservoir. This indicates that a social damage function is likely to have a convex shape in this range (Fig. 1). The convexity of the damage cost function ensures that the marginal costs are increasing with increase in the N load. The increasing concern about the water quality impairment in UBWC watershed shows that the assimilation potential has reached its limit and the N export is now in the range of convex shaped function. So we can define SDC as,

$$D = f(N_{wt}) \tag{20}$$

which is assumed to be convex, smooth and increasing with the level of the N load.

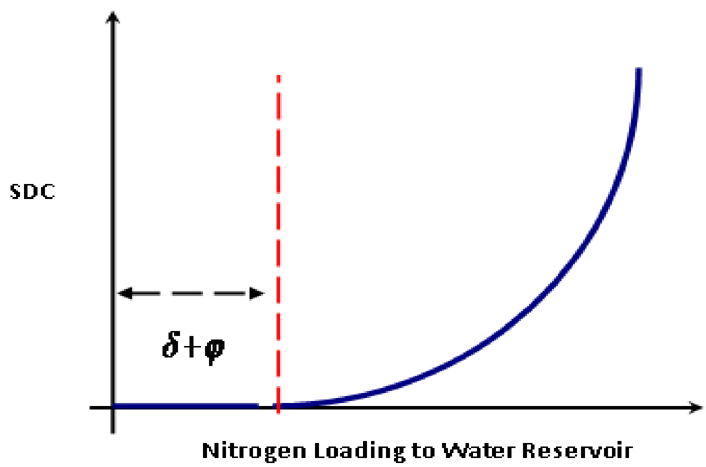

Fig. 4.1 Social damage cost curve

$$D = f(0) = 0\,, \quad \frac{\partial D(\bullet)}{\partial N_{wt}} > 0, \quad \frac{\partial^2 D(\bullet)}{\partial N_{wt}^{\;2}} > 0 \tag{21}$$

So, the equation (20) can be rewritten in the following form to fix the parameters.

$$D = \alpha(N_{wt})^{\eta} \tag{22}$$

where α is a coefficient and the exponent η is the elasticity of damage cost function. As the value for η is not readily available, a series of run was done with different values of η and α. The values considered for the analysis are 0, 0.5, 1, 1.5, 3 and 5 for α and 0, 0.5, 2 and 3 for η. To calibrate the SDC, two sets of data were used. The first data set was the recreational value of water quality benefit estimated from the second essay, which is 3.45 million (annual) if quality of the water in the watershed is improved to EPA standards. The per hectare benefit of agricultural land is calculated as $153.40. As 95 % of the recreational trips taken by the respondents were confined to the Hoover reservoir, the share of recreational benefit to streams and the Hoover reservoir was calculated as $7.67 and $145.8, respectively. The second data used to calibrate the SDC was taken from Tennity (2005). According to this study, the marginal social benefit, if N loading is reduced to half from the farm to stream, is $321.1 per hectare in the streams and $242.06 per hectare in the reservoir. With the assumption that reduction of N transport by half from farm to stream would help to achieve the EPA water quality standards for the UBWC watershed. Thereforfe, both the above-mentioned estimates were added to derive the complete marginal benefits of N reduction from farms to Hoover reservoir, which is $328.77 for streams and $387.86 for Hoover reservoir.

The complete marginal benefit calculated for the watershed ($328.77 for streams and $387.86 for Hoover reservoir) was used to parameterize α. The result of a series of analyses with different α and η values was compared with the reported value, and found that the quadratic SDC estimates were close to the previously reported value. So, the elasticity parameter was fixed as 2. From this α coefficient of SDC for water quality in the stream (N_{st}) and in the Hoover reservoir(N_{wt}) were derived, which were 0.103 and 0.19, respectively. Therefore the SDC for the stream can be written as,

$$D = 0.101(N_{st})^2 \tag{23}$$

and that for the reservoir is,

$$D = 0.19(N_{wt})^2 \tag{24}$$

Three different dynamic programs were specified for three different crop rotation scenarios. In the case of corn-soybean rotation and corn-soybean-wheat rotations, total profit is weighted with the proportion of area under each crop. Each of the dynamic programs was sequentially run for different technology scenarios.

4.2.7 Dynamic program specification

Three different DP problems were specified for C-C, C-S and C-S-W crop rotations. The Planner's problem is deterministic, with finite horizon.

- State variable:
  - Soil-N level N_t
  - Nitrate level in the downstream water reservoir N_{wt}
- State space:
  - $N_t \in [0, \infty)$
  - $N_{wt} \in [0, \infty)$
- Action variable:
  - One action variable (N application for corn) for C-C rotation DP
  - Two action variable for C-S rotation DP
    - N fertilizer application for corn and P fertilizer application for soybean
  - Three action variable for C-S-W rotation, N fertilizer application for corn.

- N fertilizer application for corn and wheat and P fertilizer application for soybean.

- Action space: $n_t \in (0, \propto]$ for both N and P fertilizers

- State Transition function:

$$AN\_\text{load}_{ij} = \left[\left(N_{\text{load}_i} \prod_j e^{\theta_{ij} \times 100}\right) \times {e_b}^{\hat{\theta}_{ij} \times 100}\right]$$

The Bellman equation can be expressed as,

$$\max_{,N_{ij}} = \left[\left(\frac{1}{1+r}\right)^t \sum_{1}^{t} \sum_{i=1}^{I} \sum_{j=1}^{J} \left[p_j \; APF_{ij} - p_N \, N_{ij} \; - p_o \; \left(APF_{ij}\right) - TechCost_{ij}\right] \right.$$
$$\left. \times \left[1 - Area_B\right] - \alpha_{wt} \left(\varphi \left(AN\_\text{load}_{ij}\left(N_{ijt-1} + n_{ijt}\right)\right)\right)^{\eta} \right]$$
$$+ V\theta \left(\delta\varphi \left(AN\_\text{load}_{ij}\left(N_{ijt-1} + n_{ijt}\right)\right)\right)$$

Where $Area_B$and φ are fraction of area under buffer and coefficient of assimilation within the stream and in the reservoir.

Coefficients of baseline production and N loading functions for C-C, C-S and C-S-W are given in Table 4.1 and coefficients of technology and crop rotation specific crop yield and N loading functions are described in the result section.

Production function	
Corn	1.615+0.082n-0.0002n^2
Soybean	1.88+0.0254 p-0.0002p^2
Wheat	1.752+0.055 n-0.0003n^2
N Balance Function	
N Uptake coefficient for C-C	0.73
N Load coefficient C-C	0.081
Soybean N_fixing coefficient	Min (80,43.53*Yield)
N Uptake coefficient for C-S	0.77
N Load coefficient C-S	0.072
Wheat uptake coefficient	0.81
Wheat N Load coefficient	0.061
Cost and Prices	
Price of Corn ($/ton)	159.74
Price of Soybean($/ton)	330.60
Price of Wheat($/ton)	146.97
Price of Nitrogen Fertilizer($/kg)	1.57
Price of Phosphorus fertilizer($/kg)	1.70
Technology Cost for split N application ($/ha)	25.00
Technology Cost for cover crop ($/ha)	110.00

Table 4.1 Coefficients of baseline production function and nutrient balance used in the model

4.2.8 Solving Bellman equation thorough collocation

We attempted to solve the problem as detailed through the collocation method, a approach for the numerical solution partial differential equations, implemented using MATLAB 7.1. In collocation technique, the basis function and number of collocation nodes in basis function has to be specified. In this exercise, we have used splin basis function and 100 collocation nodes to derive the approximation of Bellman equation. By using basis function and collocation nodes we can express the value function approximant (Miranda and Fackler, 2002). The state variables spaces (N_t and N_{wt}) were specified first, followed by the action variable. In collocation method, a state space is bounded within a specific bound on a real line. In this study, the lower bound of state space was fixed as '0' and the upper bound as 100. Then, action variable was defined as continuous, but within simple bounds, $a(s) \le x \le b(s)$. In this paper, '0' and infinity are fixed as lower and upper bounds, respectively. In CompEcon Toolbox, an approximate solution to the Bellman equation using collocation method is arrived by using following strategy:

$$V(s) \approx \sum_{j=1}^{n} c_j \phi_j(s)$$

A linear combination of n known basis functions $\phi_1, \phi_2, \phi_3, ...\phi_n$ on S (the bounded state space) and coefficients ($c_1, c_2, c_3, ...c_n$) are used to derive approximant of value function. The next step was to determine the value of these coefficients. This was done by equating the value function approximant to the Bellman equation at 100 defined collocation nodes, $s_1, s_2, s_3, ...s_{100}$. This helped us to replace the Bellman functional equation having a system of 100 nonlinear equations with 100 unknowns.

$$\sum_{j=1}^{100} c_j \phi_j(s) = \underset{x \in X(s_i)}{Max} \left\{ f(s_i, x_i) + \rho \sum_{j=1}^{n} c_j \phi_j \left(g(s_i, x_i) \right) \right\}$$

This can be expressed as,

$$v_i(c) = \underset{x \in X(s_i)}{Max} \left\{ f(s_i, x_i) + \rho \sum_{j=1}^{n} c_j \phi_j \left(g(s_i, x_i) \right) \right\} \text{ or } \Phi c = v(c)$$

Φ is collocation matrix and v is the collocation function. The collocation equation can be converted to a root-finding problem, $\Phi c - v(c) = 0$, in which the c was solved using Newton's method. All the steps were implemented using the CompEcon Toolbox routines.

4.3 Results

The coefficients of yield and N-loading functions specific to each BMP are presented in Table 4.2.

BMP Technology	Corn-Corn	Corn-Soybean		Corn-Soybean-Wheat		
	Corn	**Corn**	**Soybean**	**Corn**	**Soybean**	**Wheat**
Change in Crop Production ($\boldsymbol{\beta} \times \mathbf{100}$)						
Cons. Tillage	-0.01	-0.01	-0.02	-0.01	-0.03	-0.01
Cover Crops	-0.01	-0.01	-0.03	-0.01	-0.03	-0.03
N-Split	-0.02	-0.02	0.00	-0.03	0.00	-0.01
Buffer	0.00	0.00	0.00	0.00	0.00	0.00
N Loading by crop ($\boldsymbol{\theta} \times \mathbf{100}$)						
Cons. Tillage	-0.06	-0.06	-0.07	-0.07	-0.07	-0.02
Cover Crops	-0.07	-0.07	-0.05	-0.06	-0.06	-0.07
N-Split	-0.06	-0.07	-0.00	-0.08	-0.00	-0.07
Buffer	-0.32	-0.32	-0.32	-0.32	-0.32	-0.32

Table 4.2 Parameter values for corn-corn, corn-soybean and corn-soybean-wheat production functions

Irrespective of the technologies and crop rotations, crop yields were consistently lower than baseline yield. The differences in yield across tillage practices and crop rotations were consistent with yield variation reported by Sundermeier (2009) for Ohio, except for wheat yield in C-S-W rotation. It is reported that crop following the cover crop could experience N stress condition due to the immobilization of N, which would result in yield reduction (Wagger and Mengel, 1993). However, contrasting results were reported in terms of the effect of cover crops on soybean yield. For example, Ateh and Doll (1996) reported a positive, and Reddy (2001) and Reddy and Zablotowitz (2003) reported a negative effect of rye cover crop on the yield of following soybean crop. In addition, effect of split N application on crop yield also showed mixed results (Randall et al., 2003). Moreover, the tri-state fertilizer recommendation for corn also showed a yield reduction by split-N application (Vitosh et al., 1995). Thus, the yield reduction observed in SWAT modeling with different technologies and crop rotation were in line with previous research results.

Best Management Practices	% Adoption		
	10	40	70
	N stress days		
Cover Crop	56.88	57.53	59.11
Split-N	58.51	59.97	60.25
Conservation Tillage	56.65	58.26	59.73

Table 4.3 Nitrogen stress days under different technology simulations

It is observed that under different technology simulations in SWAT, the number of N stress days were higher under technology-scenarios as compared to that under baseline simulation of 55.28 days (Table 4.3), which is also in accordance with previous reports that indicated negative correlation between N stress days and crop yields under tillage, cover crop and split-N technologies. The N load reduction with technologies was in accordance with published research on BMP impact on reduction in nutrient loading (Dinnes et al., 2002; Kaspar et al., 2001; Randall et al., 2003).

The base run was performed with two different cases with the objective of maximizing farmer's private profit (total receipt- total variable cost).

Case-1: C-C, C-S and C-S-W crop rotations were analyzed separately. Crop rotation is represented in the DP by assigning a fraction of area as a weighing factor for each of the crop in a crop rotation. Thus, to specify C-S rotation, corn and soybean was weighted by 0.5.

	Private (Revenue-Input cost)	**Ohio**
Corn		
Yield (t/ha)	9.84	10.27
Fertilizer-N (Kg/ha)	174.5	174.26
Profit ($/ha)	558.00	476.00
Soybean		
Yield (t/ha)	2.68	3.63
Fertilizer-P (Kg/ha)	42	48
Profit ($/ha)	470	462
Wheat		
Yield (t/ha)	4.15	5.01
Fertilizer-N (Kg/ha)	80.03	92.15
Profit ($/ha)	140.16	179.04

Table 4.4 Comparison of baseline result with field crop enterprise budget-2009

However, in C-S-W rotation corn, soybean and wheat were weighted by 0.34, 0.33 and 0.33 respectively. Case-1 was attempted to compare DP derived outputs for each of the C-C, C-S and CSW rotations with the current level of agricultural production in the state of Ohio. The result was compared with the field crop enterprise budget for 2009 for crop yield, N application and profit, which showed that base run results were close to the average farm practices in Ohio (Table 4.4). In general, yields derived from DP for corn, soybean and wheat were lower than that from farm budget data for the state of Ohio. In the case of N application, the average N rate for corn obtained from DP modeling was close to that reported in farm budget for Ohio. But, the profit value, especially for corn, in DP was higher than the average profit for an Ohio farm.

Case2:

However, 90% of the cultivated area in the UBWC watershed is occupied by corn and soybean (45% each for corn and soybean). Thus, in case2 run was accomplished with C-S-W rotation with a weighing factor of 0.45 for corn and soybean and 0.1 for wheat.

		Private (Revenue-Input cost)	**Profit with internalized pollution cost**
Corn-Soybean-Wheat			
Yield (t/ha)	C	9.64	6.15
	S	2.81	2.20
	W	4.03	2.50
N load(kg/ha)		12.87	6.63
Fertilizer (Kg/ha)		170.51	103.41
DP value function ($/ha)		7950	5163
Reservoir-N (kg)		11.77	6.03

Table 4.5 Profit maximization with and without cost of pollution

The yield of corn, soybean and wheat were close to the average reported yield of the state of Ohio (Table 4.5). In addition, N- load values for C-S-W rotations were within the reported results of SWAT modeling of a watershed (Olentangy river watershed) adjacent to UBWC (Witter, 2006) and discounted profit (value function) was $7950 for C-S-W.

In the next step, the cost of pollution was accounted while calculating the profit from crop production. This could be a socially ideal case, where cost negative externality of a production process is internalized to minimize the value lost to the society due to pollution. This can be viewed as a non-point pollution taxing from government (Tax-based approach). Thus, under this case, a farmer needs to make a payment for each unit of N load that comes from his farm. The result showed that crop yield of each of the crops was reduced when cost of the pollution was internalized in profit. Moreover, nutrient load from the farm under each of the crop rotations was also reduced drastically to $ 5163 due to the reduction in fertilizer application (Table 4.5).

In the next step, model was run with Technology set-2 (C-S-W with conservation tillage, cover cropping and vegetative buffer) and Technology set-3 (N-split application with conservation tillage, cover cropping and vegetative buffer).

In the case of C-S-W rotation, N load to the reservoir was the lowest with technology set-3, which is higher than socially desirable pollution load (Maximizing profit with internalizing pollution cost). Additionally, value function and crop yields were higher than crop production with internalized cost of production scenario. However, both the technology sets crop production level and value function were less than as compared to private profit maximizing scenario. Thus, it is clear that with current crop rotation with multiple conservation technologies farmers cannot reach their private level of profit and crop production.

		Private (Revenue-Input cost)	Profit with internalized pollution cost	Technology Set-2	Technology Set-3
Yield (t/ha)	C	9.64	6.15	8.72	9.04
	S	2.81	2.20	2.41	2.35
	W	4.03	2.50	3.07	3.80
N load(kg/ha)		12.87	6.63	7.25	7.03
Fertilizer (Kg/ha)		170.51	103.41	112.46	137.48
Discounted profit ($/ha)		7950	5163	5430	5940
Reservoir-N (kg)		11.77	6.03	6.53	6.33

Table 4.6 Results after application of conservation technologies with current cultivation

Additionally, two more scenario analysis were also attempted to understand N loading under two probable crop rotation scenarios in the future,

1. Complete area under watershed follow a C-C rotation and
2. Complete area under watershed follow a C-S with each of the technology sets.

In the case of C-C rotation scenario, the N loading to the reservoir was lowest under technology set-3. Additionally, both technologies showed higher value function than that under profit maximization which accounted for cost of pollution. The N loading under the two technology sets was close to that of profit maximization which accounted cost of pollution (Table 4.7).

	Private (Revenue-Input cost)	Profit with internalized pollution cost	Technology Set-2	Technology Set-3
Yield(t/ha)	9.64	6.15	8.75	9.12
N load(kg/ha)	12.87	6.63	125.00	149.00
Fertilizer (Kg/ha)	170.51	103.41	9.50.00	11.02
Discounted profit ($/ha)	7950	5163	8037.00	8982.00
Reservoir-N (kg)	11.77	6.03	9.19	8.55

Table 4.7 Results after application of conservation technologies with C-C rotation

As far as the C-S rotation is concerned, both technology sets showed the same pattern as in C-C rotation. The yield of corn in C-S was higher than that in C-C with lower level of N application, which might be due to the availability of biologically fixed N from soybean. The value function of the C-S was lower than that of C-C rotation under both the technology cases. However, pollution load to the reservoir from both the technology sets in C-S were lesser than that of C-C rotation (Table 4.8).

	Private (Revenue-Input cost)	Profit with internalized pollution cost	Technology Set-2	Technology Set-3
Yield(t/ha)	9.64	6.15	8.75	9.12
N load(kg/ha)	12.87	6.63	6.83	7.52
Fertilizer (Kg/ha)	170.51	103.41	132.04	137.16
Discounted profit ($/ha)	7950	5163	6075.00	6132.81
Reservoir-N (kg)	11.77	6.03	6.15	6.77

Table 4.8 Results after application of conservation technologies with C-S rotation

4.4 Conclusions

A dynamic programming-based economic optimization approach was used in this study to integrate the watershed model with an economic model. The watershed modeling results from essay 1 and the benefit estimates from essay 2 were used to specify the objective and transition functions of the dynamic program. Model is developed for the entire watershed by considering it as a single homogeneous one hectare unit. The watershed model was used to simulate the baseline and conservation technology-specific production function and nutrient loading functions. Two sets of conservation technologies were developed for the watershed. One with cover cropping, conservation tillage and vegetative buffer stripes and the other with split nitrogen fertilizer application, cover cropping, conservation tillage and vegetative buffer stripes. The baseline crop production results were close to the Ohio field crop enterprise budget. In addition, N loading in baseline simulations was also in line with the modeled results of adjacent watershed. The analysis revealed that under no restriction on pollution loading, farmers would apply a maximum of 170.51kg/ha of N and the value function would be $7950 under C-S-W rotation. However, after introducing the social cost of pollution in objective function, the fertilizer application rate was reduced to 103 kg/ha. The analysis of conservation management options revealed that each of the crop rotation and technology combination would give higher value than the present level of production with internalized pollution cost. Within the crop-technology combinations, split-N application, conservation tillage, cover crop showed the lowest pollution load to the reservoir along with higher value function. Thus, it could be concluded that the present level of private profit and yield levels are not realized by adopting both the technology sets considered in this study. Additionally, more area under C-C and C-S rotation would result in more pollution load to the reservoir.

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Appendix A

Poisson, Negative Binomial, Zero-inflated Poisson and Zero-inflated Negative binomial results

Variables	Poisson		NB		ZIP		ZINB	
	β	S.E	β	S.E	β	S.E	β	S.E
Trip Model								
Constant	0.911***	0.025	0.847***	0.087	2.239***	0.026	2.052***	0.096
I	0.056***	0.008	0.129***	0.035	0.055***	0.007	0.074**	0.030
TC	-0.101***	0.003	-0.116***	0.014	-0.021***	0.003	-0.029**	0.014
FD	0.377***	0.041	0.417**	0.186	0.204***	0.041	0.186	0.161
P2D	-0.647***	0.070	-0.769***	0.221	-0.024	0.074	-0.049	0.244
P2I	-0.136***	0.022	-0.056	0.086	-0.053***	0.021	-0.022	0.081
P2TC	-0.030***	0.009	-0.086**	0.037	-0.048***	0.010	-0.055**	0.039
P2FD	-0.752***	0.116	-1.418***	0.465	-0.224**	0.116	-0.404	0.436
P3D	0.963***	0.048	0.931***	0.210	0.652***	0.050	0.751***	0.178
P3I	0.019***	0.016	0.002	0.084	0.008	0.016	-0.001	0.063
P3TC	0.001***	0.006	-0.013	0.031	-0.030***	0.006	-0.030	0.025
P3FD	-0.209***	0.078	-0.089	0.441	-0.127	0.081	-0.197	0.313
WQ	0.324***	0.042	0.393***	0.226	-0.017	0.042	-0.097	0.184
Alpha			6.465***	0.474			1.307***	0.169
Participation Model								
Constant					0.927***	0.085	-0.630***	0.113
I					-0.044	0.033	0.046	0.039
TC					0.146***	0.014	0.156***	0.017
FD					-0.455***	0.169	0.479**	0.199
P2D					0.933***	0.222	-1.04***	0.253
P2I					0.142*	0.083	-0.153***	0.099
P2TC					-0.073**	0.037	0.104**	0.045
P2FD					1.094***	0.432	-1.082**	0.502
P3D					-0.498***	0.193	0.360***	0.226
P3I					-0.047	0.077	0.062***	0.096
P3TC					-0.048	0.034	0.071*	0.043
P3FD					-0.052	0.390	0.194***	0.480
WQ					-0.704***	0.209	0.811***	0.240
-2 LL	10735		4193.9		5973		3018.1	
Tests								
LLR		Poisson and NB = 6541						
LLR		ZIP and ZINB=2976						
Vouge		Poisson and ZIP = 7.0						
Vouge		NB and ZINB = 5.4						

Commonly used recreational demand models, including Poisson (PS), Negative Binomial (NB), Zero inflated Poisson (ZIP) and Zero-inflated Negative Binomial (ZINB) were fitted to understand the best fit model for the trip data. The likelihood-ratio (LR) test was used for the comparison between PS and NB, and also between ZIP and ZINB models. Additionally, Vuong test was used for model evaluation between PS and ZIP, and also between NB and ZINB. The significance of over-dispersion parameter of NB (α = 6.47 and $p<0.0001$) suggests that PS model is not suitable for the trip data due to violation of equi-dispersion assumption (Table 2). The LR test also favored NB over PS. The critical value of 7 for Vuong test between ZIP and PS suggests that the zero trip data were generated by two processes rather than a single process (Vuong, 1989; Greene, 1994). Moreover, Vuong test also rejected NB in favor of ZINB and reaffirmed the presence of two separate processes of zero trip generation. As over-dispersion parameter (α = 1.31) of the ZINB was significant, which indicates that both zero-inflation and over-dispersion are dominant in the trip data, which is further confirmed by the LR test between ZIP and ZINB. Thus, ZINB was selected for further analysis.

Appendix B

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ADDITIONAL COMMENTS:

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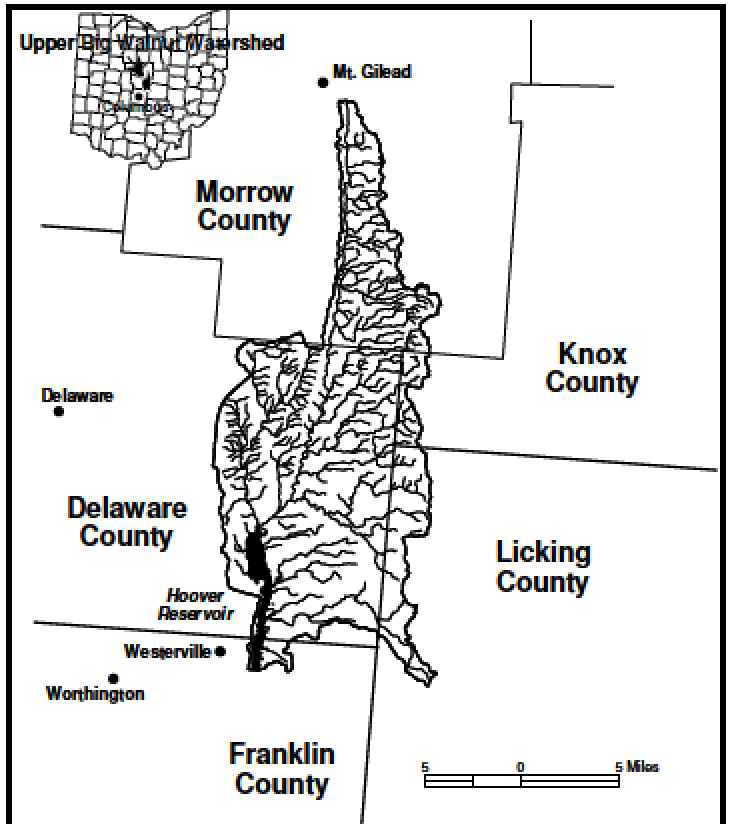
THE OHIO STATE UNIVERSITY

Please return your completed survey using the enclosed business response envelope to:
Room # 247
Department of Agricultural, Environmental and Developmental Economics
Ohio State University
2120 Fyffe Road
Columbus, Ohio 43210
: 614-292-1253

Survey for studying the impact of water quality improvements on recreational value in the Upper Big Walnut Watershed



This survey is an effort to determine the impact of Water quality improvements on recreational values in the Upper Big Walnut Watershed.

Survey on angling and other recreational values in the Upper Big Walnut Watershed

1. What is your home county and postal zip code?

   __________ (County) __________ (Zip Code)

2. I took at least one fishing trip to the Upper Big Walnut Watershed (including the Hoover Reservoir) in 2007 (see map in front page):

   ___ Yes (If "Yes" go to question **3**)

   ___ No (If "No" go to question **10**)

3. Describe the number of fishing trips you took to different zones of the Upper Big Walnut Watershed in **2007**. The zones are shown on the map on the opposite page. For this survey, a trip is considered primarily a fishing trip if fishing consumed more than 50% of your recreational time on the trip.

	Number of Fishing Trips Taken in **2007**	
	Day Trips	Overnight Trips
Zone-1, including the Hoover reservoir		
Zone-2		
Zone-3		
Zone-4		

For your typical fishing trip in the Upper Big Walnut Watershed, including the Hoover reservoir, answer the following questions. If you do not take any trips that are primarily for fishing, please skip to question **10**:

4a. How many people go with you on your typical fishing trip?

____Number of Adults ____Number of Children

4b. How many hours do you spend angling on your typical fishing trip?

____Hours per trip

 Continue on next page

For the remaining questions, please remember that this survey is completely anonymous:

22. What is your annual household income level?

____Less than $10,000 ____$50,000 to $59,999

____$10,000 to $19,999 ____$60,000 to $69,999

____$20,000 to $29,999 ____$70,000 to $79,999

____$30,000 to $39,999 ____$80,000 to $89,999

____$40,000 to $49,999 ____$90,000 or more

23. Are you retired?

____Yes ____No

24. How do you earn your income? (*Please select 1 answer only.*)

____Hourly Wage ____Salary

____Pension/Retirement Income ____Other

25. If you could work fewer hours with the same income, would you take more fishing trips during the season?

____Yes ____No

26. What is your gender?

____Male ____Female

Thank you for completing this questionnaire

18. Would additional trips within the Upper Big Walnut Watershed mean fewer trips to sites outside the Upper Big Walnut Watershed?

____Yes ____No

19. How many primarily fishing trips will you take to places outside the Upper Big Walnut watershed this year (2007)?

____Number of Day Trip ____Number of Overnight Trips

20. When you decide which recreational site to visit, how important is water quality? (*Please select 1 answer only*)

____Very important ____Important

____Somewhat Important ____Not Important

21. Use the scale below to rate how important each issue is when you decide where to fish.

1 = STRONGLY DISAGREE (SD)
2 = DISAGREE (D)
3 = NEITHER DISAGREE OR AGREE (N)
4 = AGREE (A)
5 = STRONGLY AGREE (SA)

The following are important for choosing where to fish (*circle one response per question*):

	SD	D	N	A	SA
a) Public access.	1	2	3	4	5
b) Avoiding congestion (i.e., too many people)	1	2	3	4	5
c) Nearby facilities (rest rooms, parking etc)	1	2	3	4	5
d) Natural beauty.	1	2	3	4	5
e) Probability of catching fish.	1	2	3	4	5
f) Proximity to my home.	1	2	3	4	5

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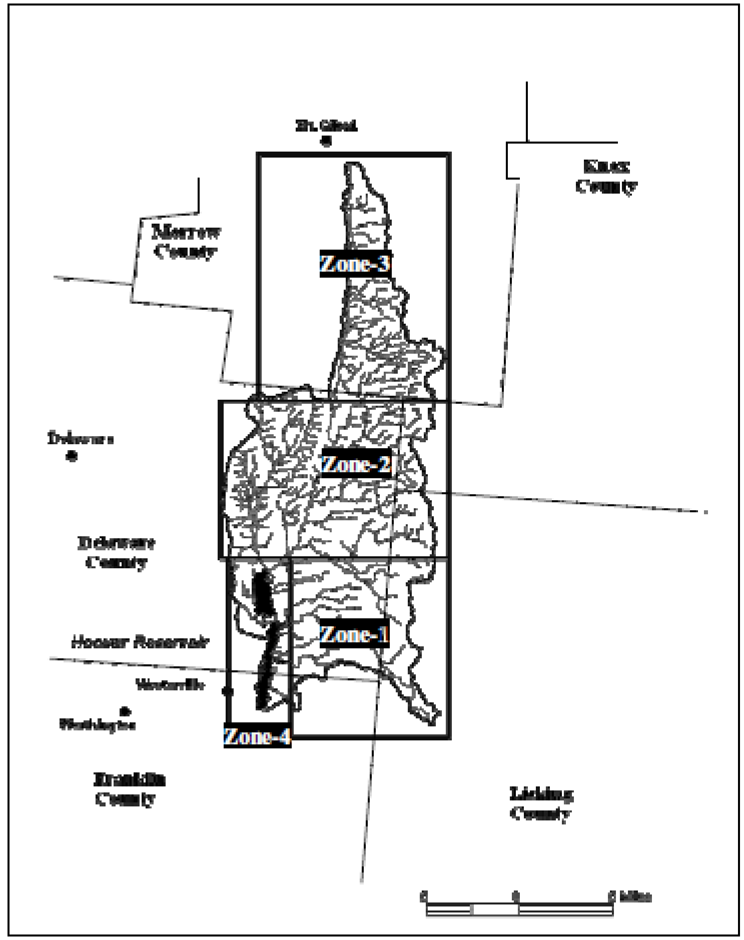
Upper Big Walnut Watershed Map



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5. What type of boat do you primarily use for fishing? (*Please select 1 answer only*)

____I do not use a boat for fishing

____Raft ____Canoe ____Kayak ____Sail

____Powerboat (Approximate size and power: _____ft and _____hp)

6. What type of fishing do you typically do in the Upper Big Walnut Watershed? (*Please select 1 answer only*)

____Fish from shore in Hoover reservoir

____Fish from boat in Hoover reservoir

____Fish in a stream from shore or wade.

____Fish in a stream from boat.

7. How many fish do you typically catch on each trip? (*Circle one response*)

0-2 3-5 6-10 11 or more

8. How many fish do you typically keep and consume each trip? (*Circle one response*)

0-2 3-5 6-10 11 or more

9. For the Upper Big Walnut Watershed site that you visit most often to fish, what is the approximate road distance between your house and that site ? Please list the name of stream or reservoir, and if possible, a more specific site location. For example, include the nearest city or major road intersection to the recreation site.

One-Way Road Distance (Miles) ___________________________

Reservoir/ Stream Name __________________________________

Specific Site Name ______________________________________

Additional information ____________________________________

Continue on next page

16. The US Department of Agriculture and other organizations spend funds each year on programs aimed at improving water quality. In addition, the Ohio Environmental Protection Agency and Ohio Department of Natural Resources have numerous programs and regulations to improve water quality.

Suppose that these programs and regulations were effective, and that they improved water quality so that 100% of streams and rivers upstream from the Hoover Reservoir were to meet water quality standards.

If water quality conditions improved and all the streams in the Upper Big Walnut Watershed, and the Hoover reservoir were to meet EPA standards for clean water quality (see map in opposite page), would you take more trips to the Upper Big Walnut Watershed and/or the Hoover reservoir?

___ Yes, I would take more trips (If "Yes" go to question 17)

___ No, I would not take more trips (If "No" go to question 19)

17. If you replied "Yes" to question 16, indicate in the table below how many **ADDITIONAL** trips you would take to the Upper Big Walnut Watershed this year (2008), with improved water quality conditions?

Recall that a trip is considered a fishing trip if fishing consumed more than 50% of your recreational time on the trip.

	Number of **ADDITIONAL** Fishing Trips in **2008** with improved Water Quality	
	Day Trips	Overnight Trips
Directly in the Hoover Reservoir		
Streams within the original **high water quality** zone near the Hoover Reservoir (not including trips to the reservoir)		
Streams and Rivers in the area **Upstream** from the Hoover Reservoir where water quality has been improved		

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Scenario of *Improved* Water Quality in the Upper Big Walnut Watershed

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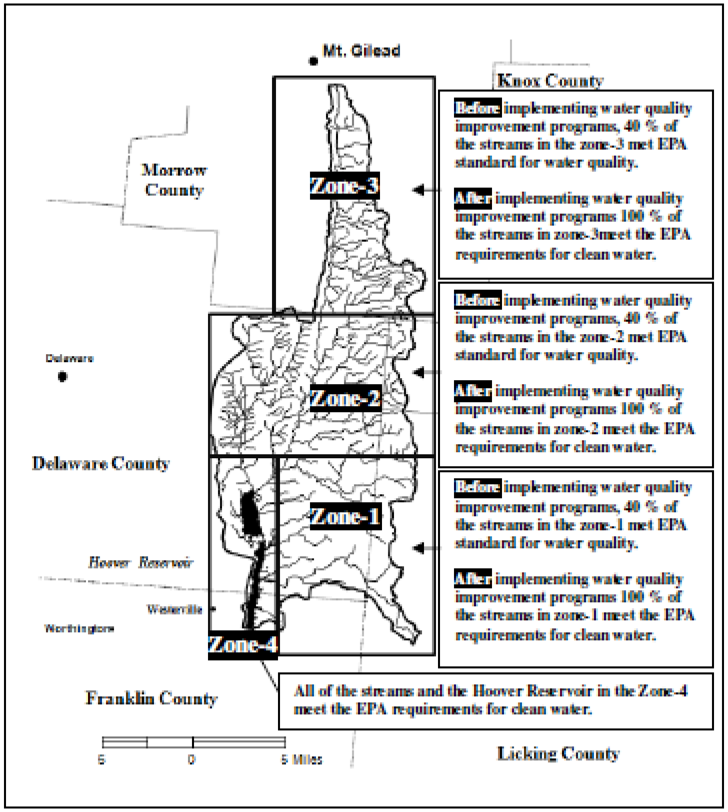
All Areas Meet or Exceed Water Quality Standards



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10. How many ***non-fishing*** recreational trips did you take within the Upper Big Walnut Watershed, including the Hoover reservoir, in **2007**? Examples of other kinds of recreational trips include: pleasure boating, sailing, jogging, hiking, birding, picnicking, hunting, etc.

    ____# of Single-Day Trips ____# of Overnight Trips

11. If you take overnight fishing trips to the Upper Big Walnut Watershed, where do you typically stay? (*Select 1 answer only*)

    ____Camp ____Stay with friends

    ____Motel/Hotel ____Other (Specify: ________________)

12. Which of the following items do you typically purchase within or near the Upper Big Walnut Watershed during your recreational trip in the watershed? (*Please select all that apply*)

    ____Beverages ____Gas ____Restaurant food

    ____Groceries ____Lodging ____Bait/Tackle

    ____Gear ____Other (Specify: ________________)

13. For the items you marked above, estimate the total amount of money you and members those with you typically spend within or near the Upper Big Walnut Watershed during your recreational trip: *(Please select 1 answer only)*

    ____< $10 ____$10-$20 ____ $20-$30

    ____$30-$40 ____$40-$50 ____> $ 50

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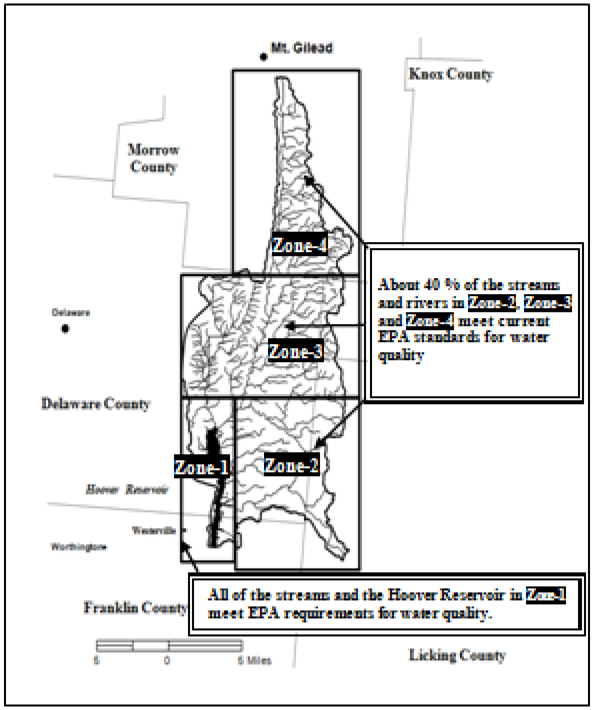
Current Water Quality Map of Upper Big Walnut Watershed

Current Water Quality Map of Upper Big Walnut Watershed



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14. The map on previous page shows current water quality of the Upper Big Walnut Watershed. The Hoover reservoir and streams in the area marked just around it currently meet or exceed water quality standards. In upstream areas, only around 40% of streams monitored meet water quality standards.

    Do you plan to take at least one fishing trip to the Upper Big Walnut Watershed (including the Hoover Reservoir) this year (2008):

    ___ Yes (If "Yes" go to question 15)

    ___ No (If "No" go to question 16)

15. If you replied "Yes" to question 14, indicate in the table below how many trips you plan to take to the Upper Big Walnut Watershed this year (2008), including any you might have already taken?

    Recall that a trip is considered a fishing trip if fishing consumed more than 50% of your recreational time on the trip.

	Number of Fishing Trips in **2008**	
	Day Trips	Overnight Trips
Directly in the **Hoover Reservoir**		
Streams within the **high water quality** zone near the Hoover Reservoir (not including trips to the reservoir)		
Streams and Rivers in the area **Upstream** from the Hoover Reservoir		

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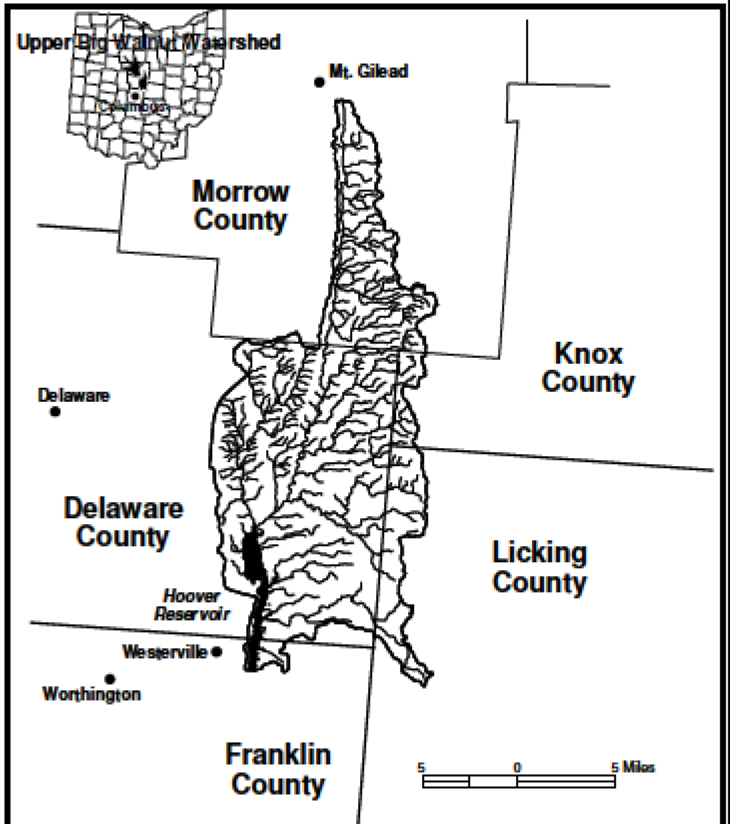
ADDITIONAL COMMENTS:

Please return your completed survey using the enclosed business response envelope to:
Room # 247
Department of Agricultural, Environmental and Developmental Economics
Ohio State University
2120 Fyffe Road
Columbus, Ohio 43210
☏: 614-292-1253

Survey for studying the impact of water quality improvements on recreational value in the Upper Big Walnut Watershed



This survey is an effort to determine the impact of Water quality improvements on recreational values in the Upper Big Walnut Watershed.

Survey on boating and other recreational values in the Upper Big Walnut Watershed

1. What is your home county and postal zip code?

__________ (County) __________ (Zip Code)

2. I took at least one boating trip to the Upper Big Walnut Watershed (including the Hoover Reservoir) in 2007 (see map in front page):

___ Yes (If "Yes" go to question **3**)

___ No (If "No" go to question **9**)

3. Describe the number of outdoor boating trips you took to different zones of the Upper Big Walnut Watershed in **2007**. The zones are shown on the map on the opposite page. For this survey, a trip is considered primarily a boating trip if you spent more than 50% of your time on the trip boating.

	Number of Boating Trips Taken in **2007**	
	Day Trips	Overnight Trips
Zone-1, including the Hoover reservoir		
Zone-2		
Zone-3		
Zone-4		

Continue on next page

For the remaining questions, please remember that this survey is completely anonymous:

21. What is your annual household income level?

____Less than $10,000 ____$50,000 to $59,999

____$10,000 to $19,999 ____$60,000 to $69,999

____$20,000 to $29,999 ____$70,000 to $79,999

____$30,000 to $39,999 ____$80,000 to $89,999

____$40,000 to $49,999 ____$90,000 or more

22. Are you retired?

____Yes ____No

23. How do you earn your income? (*Please select 1 answer only.*)

____Hourly Wage ____Salary

____Pension/Retirement Income ____Other

24. If you could work fewer hours with the same income, would you take more boating trips during the season?

____Yes ____No

25. What is your gender?

____Male ____Female

Thank you for completing this questionnaire

17. Would additional trips within the Upper Big Walnut Watershed mean fewer trips to sites outside the Upper Big Walnut Watershed?

____Yes ____No

18. How many primarily boating trips will you take to places outside the Upper Big Walnut watershed this year (2007)?

____Number of Day Trip ____Number of Overnight Trips

19. When you decide which recreational site to visit, how important is water quality? (*Please select 1 answer only*)

____Very important ____Important

____Somewhat Important ____Not Important

20. Use the scale below to rate how important each issue is when you decide where to boat.

1 = STRONGLY DISAGREE (SD)
2 = DISAGREE (D)
3 = NEITHER DISAGREE OR AGREE (N)
4 = AGREE (A)
5 = STRONGLY AGREE (SA)

The following are important for choosing where to boat (*circle one response per question*):

	SD	D	N	A	SA
a) Public access.	1	2	3	4	5
b) Avoiding congestion (i.e., too many people)	1	2	3	4	5
c) Nearby facilities (rest rooms, parking etc)	1	2	3	4	5
d) Natural beauty.	1	2	3	4	5
e) Proximity to my home.	1	2	3	4	5

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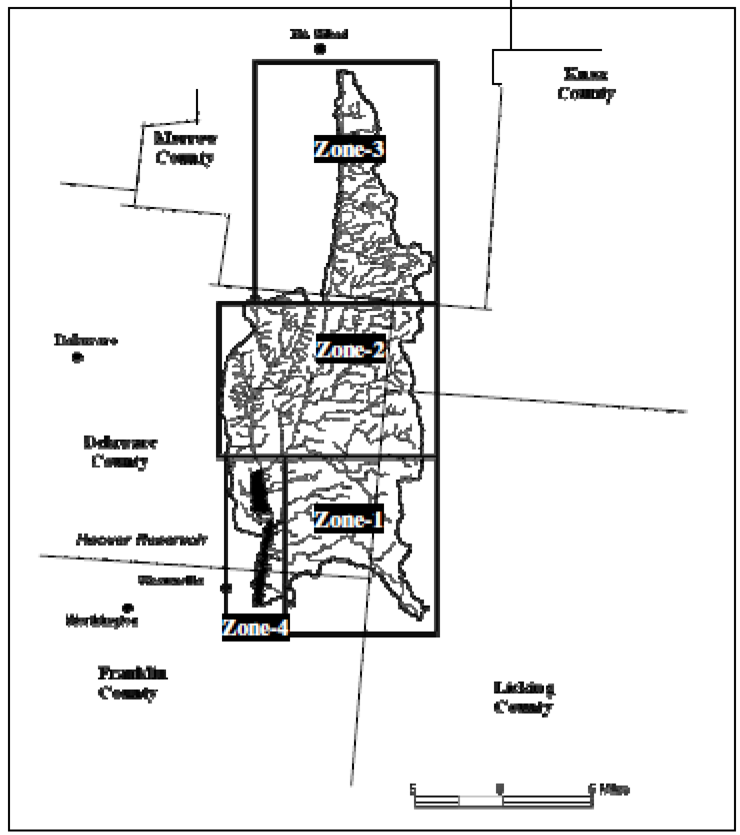
Upper Big Walnut Watershed Map



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17. Would additional trips within the Upper Big Walnut Watershed mean fewer trips to sites outside the Upper Big Walnut Watershed?

____Yes ____No

18. How many primarily boating trips will you take to places outside the Upper Big Walnut watershed this year (2007)?

____Number of Day Trip ____Number of Overnight Trips

19. When you decide which recreational site to visit, how important is water quality? (*Please select 1 answer only*)

____Very important ____Important

____Somewhat Important ____Not Important

20. Use the scale below to rate how important each issue is when you decide where to boat.

1 = STRONGLY DISAGREE (SD)
2 = DISAGREE (D)
3 = NEITHER DISAGREE OR AGREE (N)
4 = AGREE (A)
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The following are important for choosing where to boat (*circle one response per question*):

	SD	D	N	A	SA
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b) Avoiding congestion (i.e., too many people)	1	2	3	4	5
c) Nearby facilities (rest rooms, parking etc)	1	2	3	4	5
d) Natural beauty.	1	2	3	4	5
e) Proximity to my home.	1	2	3	4	5

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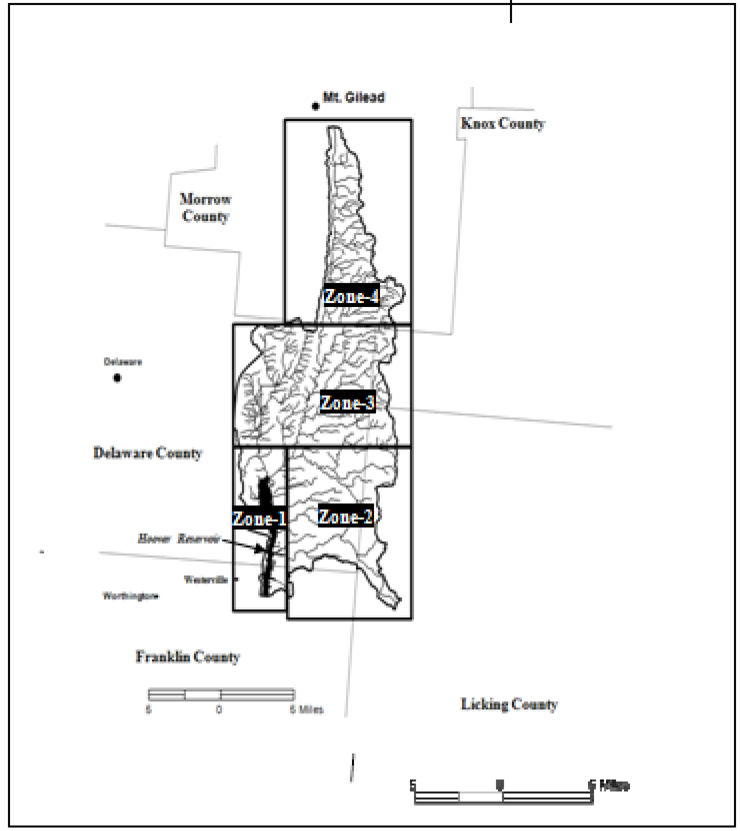
Upper Big Walnut Watershed Map



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For your typical boating trip in the Upper Big Walnut Watershed, including the Hoover reservoir, answer the following questions. If you do not take any trips that are primarily for boating, please skip to question **9**:

4a. How many people go with you on your typical boating trip?

____Number of Adults ____Number of Children

4b. How many hours do you spend angling on your typical boating trip?

____Hours per trip

5. What type of boat do you primarily use? (*Please select 1 answer only*)

____Raft ____Canoe ____Kayak ____Sail

____Powerboat (Approximate size and power: _____ft and _____hp)

6. Do you own the boat that you use most often?

____No ____Yes

7. Describe the activities you do on your typical boating trip (*Please select all that apply*):

____Water skiing ____Cruising or Paddling ____Fishing

____Swimming ___Sightseeing ___Other (Specify: ____________)

8. For the Upper Big Walnut Watershed site that you visit most often to boat, what is the approximate road distance between your house and that site ? Please list the name of stream or reservoir, and if possible, a more specific site location. For example, include the nearest city or major road intersection to the recreation site.

One-Way Road Distance (Miles) ______________________

Reservoir/ Stream Name ____________________________

Specific Site Name ________________________________

Additional information _____________________________

 Continue on next page

15. The US Department of Agriculture and other organizations spend funds each year on programs aimed at improving water quality. In addition, the Ohio Environmental Protection Agency and Ohio Department of Natural Resources have numerous programs and regulations to improve water quality.

Suppose that these programs and regulations were effective, and that they improved water quality so that 100% of streams and rivers upstream from the Hoover Reservoir were to meet water quality standards.

If water quality conditions improved and all the streams in the Upper Big Walnut Watershed, and the Hoover reservoir were to meet EPA standards for clean water quality (see map in opposite page), would you take more trips to the Upper Big Walnut Watershed and/or the Hoover reservoir?

___ Yes, I would take more trips (If "Yes" go to question 16)

___ No, I would not take more trips (If "No" go to question 18)

16. If you replied "Yes" to question 15, indicate in the table below how many **ADDITIONAL** trips you would take to the Upper Big Walnut Watershed this year (2008), with improved water quality conditions?

Recall that a trip is considered a boating trip if you spent more than 50% of your time on the trip boating.

	Number of **ADDITIONAL** Boating Trips in **2008** with improved Water Quality	
	Day Trips	Overnight Trips
Directly in the Hoover Reservoir		
Streams within the original **high water quality** zone near the Hoover Reservoir (not including trips to the reservoir)		
Streams and Rivers in the area **Upstream** from the Hoover Reservoir where water quality has been improved		

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Scenario of *Improved* Water Quality in the Upper Big Walnut Watershed

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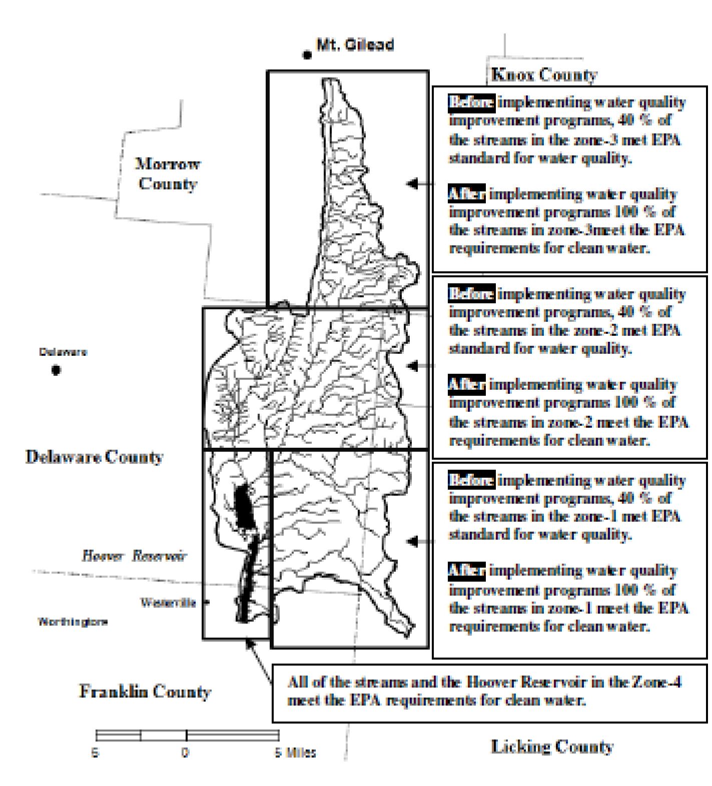
All Areas Meet or Exceed Water Quality Standards



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9. How many ***non-boating*** recreational trips did you take within the Upper Big Walnut Watershed, including the Hoover reservoir, in **2007**? Examples of other kinds of recreational trips include: jogging, hiking, birding, picnicking, hunting, etc.

    ____# of Single-Day Trips ____# of Overnight Trips

10. If you take overnight boating trips to the Upper Big Walnut Watershed, where do you typically stay?

    ____Camp ____Stay with friends

    ____Motel/Hotel ____Other (Specify: ________________)

11. Which of the following items do you typically purchase within or near the Upper Big Walnut Watershed during your recreational trip in the watershed? (*Please select all that apply*)

    ____Beverages ____Gas ____Restaurant food

    ____Groceries ____Lodging ____Bait/Tackle

    ____Gear ____Other (Specify: ________________)

12. For the items you marked above, estimate the total amount of money you and members those with you typically spend within or near the Upper Big Walnut Watershed during your recreational trip: *(Please select 1 answer only)*

    ____< $10 ____$10-$20 ____ $20-$30

    ____$30-$40 ____$40-$50 ____> $ 50

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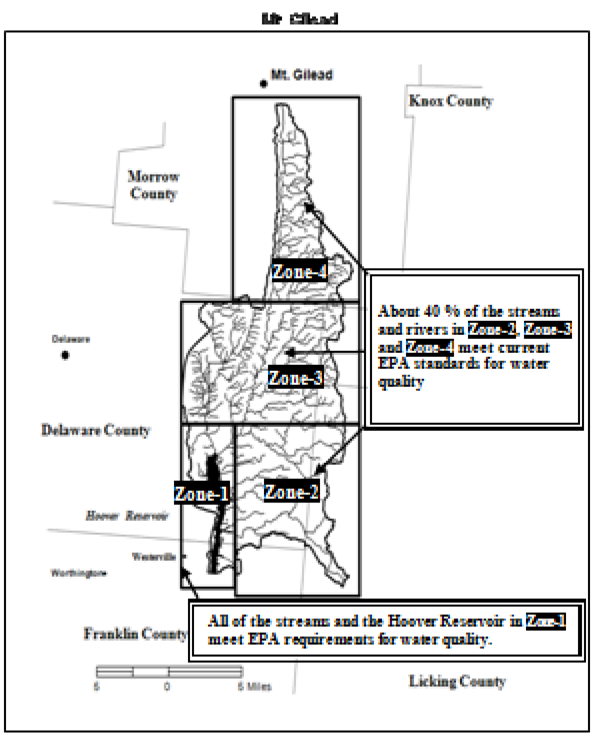
Current Water Quality Map of Upper Big Walnut Watershed



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13. The map on previous page shows current water quality of the Upper Big Walnut Watershed. The Hoover reservoir and streams in the area marked just around it currently meet or exceed water quality standards. In upstream areas, only around 40% of streams monitored meet water quality standards.

    Do you plan to take at least one boating trip to the Upper Big Walnut Watershed (including the Hoover Reservoir) this year (2008):

    ___ Yes (If "Yes" go to question 14)

    ___ No (If "No" go to question 15)

14. If you replied "Yes" to question 13, indicate in the table below how many trips you plan to take to the Upper Big Walnut Watershed this year (2008), including any you might have already taken?

    Recall that a trip is considered a boating trip if you spent more than 50% of your time on the trip boating.

	Number of Boating Trips in **2008**	
	Day Trips	Overnight Trips
Directly in the Hoover Reservoir		
Streams within the **high water quality** zone near the Hoover Reservoir (not including trips to the reservoir)		
Streams and Rivers in the area **Upstream** from the Hoover Reservoir		

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