Water and well-being: Advances in measuring the value of water quality to people

A Dissertation

SUBMITTED TO THE FACULTY OF

UNIVERSITY OF MINNESOTA

BY

Bonnie L. Keeler

IN PARTIAL FULFILLMENT OF THE REQUIREMENTS

FOR THE DEGREE OF

DOCTOR OF PHILOSOPHY

Adviser Stephen Polasky, Co-adviser Jason Hill

December 2013

Acknowledgements

I gratefully acknowledge the contributions of my many colleagues at the Institute on the Environment and the Natural Capital Project. Particular thanks to my dissertation committee of Steve Polasky, Jason Hill, Jacques Finlay, and Steven Manson. For my work on water quality valuation presented in Chapter One I acknowledge the contributions of Kate Brauman, Kris Johnson, Brent Dalzell, Kent Kovacs, Ann O'Neill, and Jacques Finlay. Additional insights on Chapter One were provided by Catherine Kling, John Downing, Lisa Schulte-Moore, Robert Johnston, John Linc Stine, Steve Taff, Larry Baker, Susie Carlin, Brooke Hacker, Ken Brooks, Joe Magner. Joe Fargione, Jason Hill, and Daniel Hernandez. On Chapter Two, I am grateful for the assistance of Bob Tipping and Tony Runkel of the Minnesota Geologic Survey, Terry Lee of the Olmsted County Planning Department and Martin Bezener for assistance with statistical analysis. On Chapter Three, I acknowledge Molly Wynia for assistance with the route analysis, Christopher Filstrop for Iowa lake water quality data, Cathy Kling and John Downing for lake visitation data from the Iowa Lakes Project, Pam Anderson and Steven Heisarky for data on Minnesota lake water quality, Spencer Wood for providing the Flickr photo data for Minnesota and Iowa lakes, Martin Bezener for assistance with statistical analysis, and Martha Rogers and Justin Johnson for help with cost estimates. Funding to support my research was provided by a National Science Foundation Graduate Research Fellowship, an Institute on the Environment Interdisciplinary Doctoral Fellowship, an EPA Science To Achieve Results (STAR) Fellowship, and the Kenneth Grant Soil and Water Conservation Society Fellowship.

Abstract

Water quality is declining in many parts of the world due to land-use change, pollution, and other stressors. In addition to the ecological impacts of these changes, water quality also affects the provision of multiple ecosystem goods and services including human health, recreation, and livelihoods. Investments designed to protect or restore water quality can be expensive and decision-makers must weigh the costs of new regulations against the public benefits provided by clean water. In order to make informed decisions regarding the management of our land and water resources, we need information on the ways that changes in water quality affect human well-being and the economic value of those changes. In Chapter One I address this gap by introducing a comprehensive framework for the valuation of water quality-related ecosystem services. In Chapter Two I apply this framework to an investigation of land-use change and consequences to groundwater quality and find that grassland conversion to agriculture is likely to result in significant costs to private well owners. In Chapter Three I use geo-tagged social media to assess visitation patterns to recreational lakes and find that lake users visit clear lakes more frequently and travel further to lakes with greater water quality. Using interdisciplinary approaches that are both generalizable and scalable, my work highlights the real costs associated with changes in water quality and in doing so addresses an important information gap needed to support environmental decision-making.

Table of Contents

List of Tables

List of Figures

Introduction

Environmental decision-making in a dynamic world

Decision-makers are increasingly called upon to make decisions with respect to land-use or resource management in which there is both incomplete information and great uncertainty surrounding potential future outcomes (Polasky et al. 2011a). Sociologists have called these problems examples of "post-normal science" where decisions need to be made before "normal" science has come to a resolution about the major drivers and underlying system dynamics (Kuhn 1962, Funtowicz and Ravetz 1993). Decisions are further complicated when the interests of different stakeholder groups are at odds or linked to controversial policies or programs. These situations are pervasive in conservation and land management today and represent one of the greatest challenges to the successful integration of science and policy.

Despite these challenges, science plays an important role in ensuring that accurate and relevant information is available to decision-makers, even in situations of great uncertainty. The criteria for research under the "post-normal science" paradigm is therefore not to study the problem until enough is known to make the right decision, but rather contributing information such that it increases the likelihood that a slightly better decision is made than in the absence of additional information. This requires synthesizing information from different studies and contexts to inform generalizable models, simplifying complex ecological processes to capture only the most important variables, and creating models that are sensitive to the types of actions or policies under consideration by decision-makers.

In addition to creating simplified and generalizable tools to inform decision-making, results of these models need to be placed in an evaluative context that provides clues to the larger significance of the data (Norton 1998). A value-based description that describes a socially desirable state of the ecosystem carries more weight than ecological terms like "productivity" or "nutrient retention". Linking environmental changes to impacts on human well-being highlights the dependence of our health, recreation, and livelihoods on functioning, resilient ecosystems (Daily 1997). Applying anthropocentric definitions of value to ecological systems and processes is not without controversy (McCauley 2006). Yet many researchers advocate that "without such valuations, however incomplete, contingent, or uncertain, ecological values will most often lose to those for which markets, laws, local control, and culture provide measures in comparable currencies of value" (Hulse and Ribe 2000).

Ecosystem services and full-cost accounting

The choices society makes about development, restoration, land use and land management have consequences for natural systems and the valuable goods and services provided by ecosystems (MA 2005). Some of these goods and services, such as agricultural production or timber, are private goods for which values can be approximated from markets. However, environmental change results in changes in many other public goods for which markets do not exist to capture their values. These goods include changes to air and water quality, carbon sequestration, wildlife habitat, and aesthetic values. This creates a situation where the values of both positive and negative externalities associated with decisions are poorly captured and therefore are often ignored in decision-making.

The emerging field of ecosystem services assessment and valuation was developed to address the need for more comprehensive accounting of the consequences of actions or decisions. Today, there is increasing demand for tools and approaches that allow researchers and decision-makers to assess the provision and value of ecosystem services and the impacts of human activities on those values. A suite of models are now available for assessing the production and value of ecosystem services (Tallis and Polasky 2009, Villa et al. 2009, Nelson and Daily 2010). Several recent studies have demonstrated the potential of ecosystem services information to inform conservation, spatial planning, and natural resource decision-making (Nelson et al. 2008, Nelson et al. 2009, Liu et al. 2010, Euliss Jr et al. 2011, Perrings et al. 2011, Polasky et al. 2011b).

Despite broad recognition of the value of the goods and services provided by nature, existing tools for assessing and valuing ecosystem services often fall short of the needs and expectations of decision-makers. One of the fundamental challenges of mainstreaming ecosystem services into decision-making is linking biophysical models of ecosystem processes with impacts on human well-being (Carpenter et al. 2009). For some services, establishing the relationship between service provision and human utility is fairly straightforward. As noted above, agricultural crops and timber are products of natural systems that are directly consumed by humans and have a market value. For other services, the challenges associated with linking biophysical and economic models are much greater. If we continue to limit ecosystem service assessment to services with clear approaches to assessment and valuation we systematically undervalue ecosystem services and prevent a full cost accounting of all the environmental and economic tradeoffs associated with decisions.

Dissertation Overview

My research addresses the need for a new generation of tools for improved decision-making with respect to ecosystem services. The types of decision contexts I am targeting include land-use or land management decisions, cost benefit assessments for environmental regulations, and spatial planning for restoration or conservation activities. Informing decision-making in these contexts requires synthesizing knowledge from both the natural and social sciences, developing integrated biophysical and economic models, and utilizing data and approaches that are scalable, generalizable, and low cost.

For my dissertation I focus on the suite of ecosystem services related to water quality. Water quality-related services are perhaps the most important missing component in our current ecosystem services toolbox. Water quality has received considerably less attention than air quality in the general economic literature (Olmstead 2010). Information on the value of water quality is needed to inform cost benefit assessments, regulatory analyses, and spatial planning (Griffiths et al. 2012). However, there has been no consistent framework for estimating changes in water quality-related services or assigning an economic value to changes in quality. The lack of a clear approach to characterize water quality-related services is a barrier to comprehensive ecosystem service assessment and valuation.

There are several challenges underlying the valuation of water quality that have made it difficult to come up with a unifying framework for assigning economic value to changes in quality. Water quality encompasses a broad suite of contaminants, including nutrients, toxins, temperature changes, sediments, and other pollutants, which can affect lakes, rivers, streams, wetlands, estuaries, and coastal endpoints. To fully capture all of the impacts associated with an action that affects water quality, researchers need to consider the broad suite of constituents and the diverse endpoints that may be impacted. Actions that affect water quality are often separated by space and time from the locations and individuals that are then affected by changing quality, making it difficult to deduce general patterns across regions, services, and drivers of change. For example, a change in agricultural management in one watershed can have both local effects on drinking water quality and downstream effects on algal blooms and commercial fisheries in coastal areas. Finally, valuation requires the challenging task of integrating ecological, hydrological, and economic models. The relationships that drive changes in water quality and subsequent changes in ecosystem services are often subject to thresholds and non-linearities making them complex processes that are difficult to model with simple tools.

In my first chapter (Keeler et al. 2012) I present a framework for water quality valuation that addresses many of the shortcomings of existing work on water quality valuation. My approach links actions to changes in water quality, changes in water quality to changes in human well-being and changes in economic value. I delineate the full suite of ecosystem services related to water quality and then present a template for water quality valuation that separates water quality into individual services that affect unique endpoints and beneficiaries. I outline the appropriate inputs and outputs of integrated biophysical and economic models and refer to existing data sources and models that can be used to link actions all the way to economic value.

The framework presented in Chapter One lays the groundwork for the dissertation. I identify the most important water quality-related services, review the ecological and economic science related to the provision and value of each service, and highlight key data gaps that are barriers to decision-making. In Chapters Two and Three I address two of these data gaps by applying the framework presented in Chapter One to case studies in water quality valuation.

In Chapter Two I investigate the value of water quality changes associated with grassland conversion to agriculture. I use a logistic regression approach to estimate how land-use change affects the probability of groundwater contamination by nitrate in private drinking water wells in southeast Minnesota. I find that recent (2007 to 2012) grassland loss to agriculture in southeastern Minnesota is expected to increase the future number of wells exceeding 10 ppm nitrate-nitrogen by 45% (from 888 to 1,292 wells). I link outputs of the groundwater well contamination model to cost estimates for well remediation, well replacement, and avoidance behaviors to estimate the potential economic value lost due to nitrate contamination from land-use change. I estimate \$2.1 to 12.2 million in costs over 20 years to address the increased risk of nitrate contamination of wells. My approach demonstrates how biophysical and economic approaches can be integrated to estimate the ecosystem service consequences of land-use change.

In Chapter Three I address the need for information on the value of water quality to lake recreation. Regulatory authorities such as the Environmental Protection Agency (US EPA) and state agencies in charge of managing water resources need approaches to value of the public benefits that would result from additional investments in improving surface water quality. I present a method to assess the value of changes in water quality to lake recreation using geo-tagged photographs as a proxy for visitation. I find that improved lake water clarity is associated with greater lake visitation and that lake users are willing-to-pay greater travel costs to visit clearer lakes. We estimate a one-meter increase in lake water clarity is associated with $22 in increased willingness-to-pay per lake visitor and would generate 1,094-1,183 additional annual visits per lake.

Research impacts

Producing science that is relevant to decision-makers is challenging. Great uncertainty on the underlying drivers of complex ecological processes, as well as mismatches in the temporal and spatial scales of data and stakeholder information needs, make translating research to generalizable tools very difficult. However, the scale of human impacts on ecosystems and the growing need for information on how to balance economic development, conservation, and impacts of decisions on human well-being requires improved integration of science and decision-making. These three chapters introduce methods to more comprehensively assess the impacts of proposed actions or policies on the values of water quality-related ecosystem goods and services.

Chapter One

Linking water quality and well-being for improved assessment and valuation of ecosystem services

Despite broad recognition of the value of the goods and services provided by nature, existing tools for assessing and valuing ecosystem services often fall short of the needs and expectations of decision-makers. Here I address one of the most important missing components in the current ecosystem services toolbox: a comprehensive and generalizable framework for describing and valuing water quality-related services. Water quality is often misrepresented as a final ecosystem service. I argue that it is actually an important contributor to many different services, from recreation to human health. I present a valuation approach for water quality-related services that is sensitive to different actions that affect water quality, identifies aquatic endpoints where the consequences of changing water quality on human well-being are realized, and recognizes the unique groups of beneficiaries affected by those changes. I describe the multiple biophysical and economic pathways that link actions to changes in water quality-related ecosystem goods and services and provide guidance to researchers interested in valuing these changes. Finally, I present a valuation template that integrates biophysical and economic models, links actions to changes in service provision and value estimates, and considers multiple sources of water quality-related ecosystem service values without double counting.

Introduction

One of the fundamental challenges of mainstreaming ecosystem services into decision-making involves linking ecosystem processes with changes in human well-being (Bateman et al. 2011). This is especially true for water quality-related ecosystem goods and services. Water quality is highly valued by the public, and information on water quality values is increasingly demanded by decision-makers. However, there is currently no generalizable framework for linking changes in water quality to changes in multiple ecosystem goods and services. If we limit ecosystem service assessments to those services with direct use value and market prices we systematically undervalue ecosystem services and fail to achieve a full accounting of all the environmental and economic tradeoffs associated with decisions.

Valuing water quality changes is particularly challenging relative to other ecosystem goods and services. Changing water quality affects many aspects of human well-being and benefits and/or costs accrue to different groups of beneficiaries at varying spatial and temporal scales. This complexity contrasts with the ecosystem services of carbon sequestration where emissions are aggregated into a global atmospheric pool. As a result, each unit increase in carbon emissions results in a more or less constant loss in value (i.e. costs associated with climate change). By contrast, each unit improvement in water quality may impact only a local area, the value of which varies widely with spatial context and may have strongly diminishing marginal benefits within the local context (e.g. additional reductions in nutrient pollution entering a clean lake generate minimal new benefits, and those benefits are further influenced by the condition and proximity to substitute lakes). Further, actions today can affect water quality far into the future with the consequent challenge of predicting future values.

High uncertainty and lack of appropriate data to populate biophysical and economic models are also barriers to comprehensive water quality valuation. Water quality affects people through numerous pathways from drinking water to recreation. The consequences of decisions on the provision of water quality-related ecosystem services are often separated by space and time, modified by variation in baseline conditions and characterized by non-linearities and thresholds (Scheffer et al. 1993, Scheffer et al. 2001). The value of ecosystem services, especially for cultural and aesthetic values, is also likely to be uncertain.

Previous work has made progress in identifying sources of water quality value and in developing economic approaches to valuation, but current water quality valuation tools fall short of the needs and expectations of decision-makers. First, most water quality valuation assessments do not account for the multiple costs and/or benefits of water quality-related changes. Recent assessments of the water quality impacts of bioenergy policy in the U.S. (see Donner and Kucharik 2008, Secchi et al. 2011, Costello et al. 2009) focus solely on the contribution of fertilizer-derived nitrogen to hypoxia in the Gulf of Mexico, neglecting other potential consequences for drinking water treatment costs, human health, and diminished recreational opportunities. Failure to consider all of the water quality-related consequences for well-being can lead to a serious underestimate of the true value of changes in ecosystem services associated with a given action or decision.

A second shortcoming of existing work on water quality valuation, and ecosystem services research in general, is that valuation assessments often are not linked with changes in management, land use, or other actions that lead to water quality change (Fisher et al. 2008). Assessments of the total costs of eutrophication (e.g. Dodds et al. 2009) or the total value of ecosystem services from an ecosystem or land cover type (e.g. Costanza et al. 1997, Liu et al. 2010) do little to help a decision-maker trying to assess the consequences of alternative actions. The value attributable to conserving wetlands for improved sediment retention, for example, needs to be assessed relative to a specified alternative land cover or management action (i.e. draining wetlands for agriculture or urban development). Decision-makers need models that are sensitive to the variation in local ecological conditions that affect the provision of ecosystem services, as well as to variation in local social and economic conditions that affect the value of ecosystem services to beneficiaries. By failing to link valuation estimates with specific actions and subsequent changes in human well-being, researchers also risk double-counting of value (Boyd and Banzaf 2007).

Finally, economic models for valuing water quality-related ecosystem services are often poorly integrated with ecological and hydrologic models. Biophysical and economic models are typically developed in isolation without consideration of how the outputs of one model may feed into the next, making it challenging to integrate models and data. For example, the water quality metrics most commonly measured by scientists are not well-connected with attributes the public actually values (e.g. people value the extent to which they can safely use and enjoy a lake, they do not directly value the concentration of phosphorus in the lake).

A framework for water quality valuation

I propose a new framework for the assessment and valuation of water quality-related services that addresses many of the shortcomings of existing work on water quality valuation. My approach is comprehensive, integrates biophysical and economic research, is sensitive to alternative land use or management decisions, and avoids double counting of costs or benefits. To maximize the potential utility for decision-making, the framework links actions to a measured or modeled change in water quality and then to changes in the value of ecosystem goods and services (Figure 1).

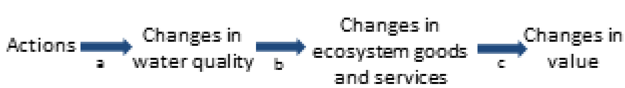


Figure 1: Framework for linking actions to values for water quality-related ecosystem services.

Biophysical models inform the linkage between actions or changes on the landscape and a change in water quality (Figure 1a) as measured by changes in nutrient concentrations, sediment loading, or inputs of toxins or other chemicals. Models focusing on the characterization of changes in water quality include continuous daily time step models such as the Soil and Water Assessment Tool (SWAT, Arnold et al. 2005) and less complex models such as the Integrated Valuation of Ecosystem Services and Tradeoffs (InVEST, Tallis et al. 2011). These models have been used to estimate the water quality consequences of future land use scenarios (Nelson et al. 2009) or the effectiveness of conservation policies (Euliss et al. 2011). Outputs from the biophysical models may be expressed in terms of nutrient retention across a landscape or in loadings to specific aquatic endpoints.

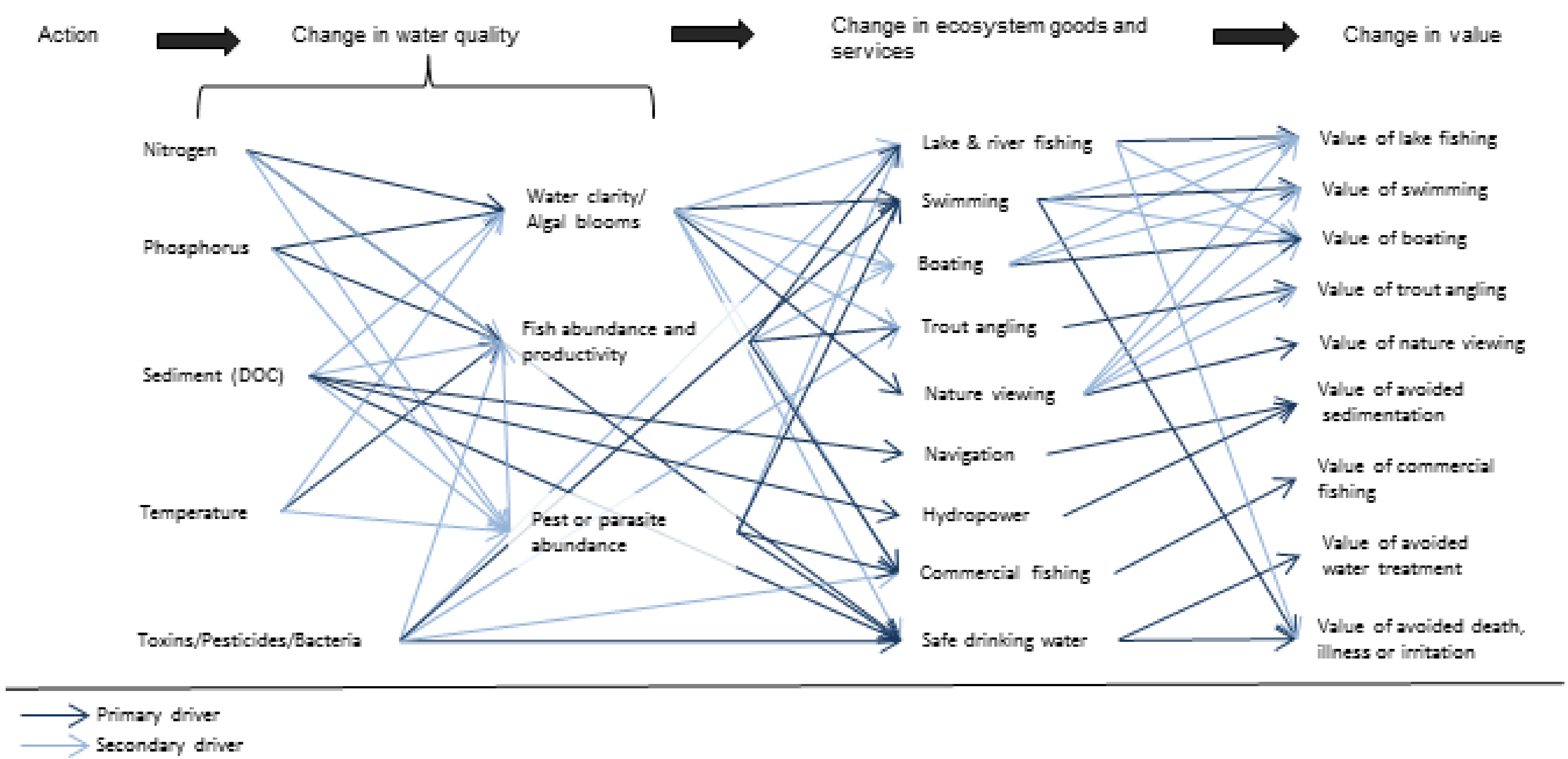
The second step in my framework (Figure 1b) links changes in water quality to changes in the provision of ecosystem goods and services that directly affect human well-being. Lack of appropriate models or data to describe this link often limits the potential to successfully integrate biophysical and economic models. Ideally, biophysical models would translate water quality changes to valued goods and services such as changes in catch per unit effort of fishes, frequency of beach closures, or the toxicity of harmful algal blooms. However, many of these relationships are either poorly understood, difficult to generalize, or we lack the data to quantify the relationships. Specificity is also an important part of this linkage: water quality affects many different aspects of human well-being, so a change in one water quality constituent may affect different beneficiaries at varying spatial and temporal scales.

The final linkage in the framework (Figure 1c) connects changes in ecosystem goods and services to changes in values. There are numerous approaches employed by economists to place an economic value on water quality-related ecosystem services (Bockstael et al. 2000, Johnston et al. 2005, Phaneuf and Smith 2005, Thompson and Segerson 2009). In brief, economists can ask respondents directly how much they would be willing to pay for a given improvement in water quality (stated preference methods). Alternately, economists can indirectly estimate the value of changes in water quality through observations of human behavior such as willingness to drive longer distances to visit areas of higher water quality or willingness to pay for property neighboring waters of higher quality (revealed preference methods). Other approaches include estimating the costs avoided by improving water quality (e.g., sediment dredging, drinking water treatment), or the costs associated with increased health risks due to contact or consumption of unsafe water. In addition, valuation methods typically generate estimates of value held by people today given current conditions and not a dynamic assessment of values of changes in the flow of ecosystem services through time. Reviews of economic approaches to water quality valuation are provided by Wilson and Carpenter (1999), Brauman et al. (2007), and Griffiths et al. (2012).

Delineating the multiple ecosystem services associated with water quality

Defining water quality as multiple biophysical metrics that may influence the provision of many different "final" ecosystem services is critical for comprehensive valuation (Boyd and Banzaf 2007). In Figure 2 I chart the potential interactions between changes in water quality and multiple ecosystem services. A single action that affects water may cause a change in another attribute, such as water clarity, or have a direct effect on the provision of various ecosystem services that affect different groups of beneficiaries. Figure 2 builds the on the general framework introduced by the Millennium Ecosystem Assessment (2005) that links ecosystem services to constituents of well-being while adding specificity for water quality-related services.

Figure 2: Relationships between water quality change, multiple ecosystem goods and services, and associated changes in values. Actions considered in the far left column include changing land use or land management as well as other drivers of water quality change such as climate change, invasive species, and atmospheric deposition. Connections between columns are classified as primary or secondary based on expert opinion. While not representative of all possible water quality changes, pathways, and effects on well-being, the figure highlights the most important and often-measured services.



Action
Change in water quality
Change in ecosystem goods and services
Change in value
Nitrogen
Phosphorus
Sediment (DOC)
Temperature
Toxins/Pesticides/Bacteria
Water clarity/ Algal blooms
Fish abundance and productivity
Pest or parasite abundance
Lake & river fishing
Swimming
Boating
Trout angling
Nature viewing
Navigation
Hydropower
Commercial fishing
Safe drinking water
Value of lake fishing
Value of swimming
Value of boating
Value of trout angling
Value of nature viewing
Value of avoided sedimentation
Value of commercial fishing
Value of avoided water treatment
Value of avoided death, illness or irritation
Primary driver
Secondary driver

Few water quality-related services are affected by just one action, and many services in combination cause changes in value (Figure 2). For example, the value of lake fishing is affected by changes in fish abundance and species composition but may also be influenced by water clarity and/or the prevalence of toxins that lead to fish consumption advisories. Fish abundance, in turn, is driven by changes in phosphorus and is influenced by nitrogen, temperature, sediments, toxins, and interactions with other organisms. There may also be feedbacks among services such that a change in the provision of one service affects the provision of another service (e.g., a change in lake fishing may also affect the value of boating).

Figure 2 also illustrates how a single change in one water quality constituent can affect multiple ecosystem services and numerous sources of value. Changes in nitrate loading are most commonly associated with changes in the extent and duration of coastal hypoxia and with the health risks of methemoglobinemia, often called blue-baby syndrome (Comly 1945, Fan et al. 1987). However, changes in nitrate can also affect the prevalence of water-borne disease-causing organisms, and even low levels of nitrate in drinking water can lead to increased health risks (Ward et al. 2011, Weyer et al. 2008). Therefore, the total value associated with a change in the quality of drinking water includes both the cost of removing nitrate from drinking water and any loss in value associated with increased health risks from consuming water with nitrate levels that are high but below the drinking water standard. Additional negative commercial or recreational consequences associated with hypoxia or harmful algal blooms would add to the lost value attributable to a single action (e.g., increased nitrogen fertilizer added upstream).

A template for the assessment and valuation of water quality-related services

Based on the services and interactions mapped in Figure 2, I present a template for integrated biophysical and economic modeling for comprehensive water quality valuation. For each constituent of water quality change (nitrogen, phosphorus, sediment, etc.), the template identifies the water quality attribute most commonly valued by people, the endpoint and beneficiaries to be measured or modeled, and appropriate economic valuation approaches

Figure 3: Template for water quality valuation based on integrated biophysical and economic models. Each row in the table represents a water quality change that affects an endpoint and groups of beneficiaries in a unique way such that there is no overlap in value. Value estimates generated by each row in the template can be summed for an estimate of the value generated or lost by a given action or scenario. For some service estimates (e.g. lake recreation), users will need to select a single valuation tool (e.g. hedonic model or recreation demand model) listed in the cell to avoid double-counting value because there may be overlap in the groups of beneficiaries if multiple approaches are applied to the same water quality change (e.g. lakeshore property owners may also be lake recreationists). The examples given in the template are not meant to be a complete enumeration of all services but rather are provided as illustrative examples of the steps involved in an integrated approach.

Biophysical Modeling **Economic Modeling**

Ecosystem Service	Change in Constituent	Endpoint	Change in Valued Attribute	Beneficiaries	Valuation Approach
Lake recreation	P	Lakes	Water clarity	Lake recreationists Lakeshore property owners	Recreational demand model Willingness to pay for recreation Hedonic pricing
Clean drinking water	N	Source water treatment facilities	[Nitrate] above 10ppm	Treatment facility & taxpayers	Avoided treatment costs for nitrate
Clean drinking water	N	Groundwater	[Nitrate] above 10ppm	Well owners	Avoidance costs (bottled water) Remediation costs (treatment) Replacement costs (new well)
Clean drinking water	N	Drinking water (surface or groundwater)	[Nitrate]	Consumers, particularly at-risk subpopulations	Increased risk of disease * value of statistical life/health Avoidance costs
Commercial fisheries	N	Bays, estuaries, gulf	Fish and shellfish productivity	Fish and shellfish industry and consumers	Fishery rents Value per unit fish/shellfish
Beach recreation	N	Ocean beaches	Algal blooms	Beach recreationists	Beach closures Willingness to pay for recreation Recreational demand model
Safe contact with water	N	Inland beaches	Aquatic pests and parasites	Swimmers	Avoidance costs Irritation/health costs
Trout angling	Stream temperature	Coldwater streams	Trout abundance or habitat area	Anglers	Willingness to pay per fish or per unit area habitat Recreational demand model
Avoided sedimentation	Sediment	Reservoirs, Lakes	Amount of sediment	Taxpayers, watershed managers, commercial, navigation	Avoided costs (dredging)
Safe drinking water	Sediment Dissolved organic carbon (DOC)	Source water treatment facilities	[DOC]	Treatment facility & taxpayers	Avoided treatment costs (DOC can react with chlorine to form suspected carcinogens)
Safe drinking water	Toxins/ Bacteria	Drinking water (surface or groundwater)	[toxin]	Consumers	Increased risk of disease * value of statistical life/health Avoidance behavior costs
Safe contact water	Toxins/ Bacteria	Swimming areas	[toxin]	Swimmers	Increased risk of disease * value of statistical life/health Avoidance costs

Researchers interested in assessing water quality-related services and economic values can use the template to identify model requirements, key data needs, and existing tools and approaches for water quality valuation. There are five steps to using the template:

1. *Identify actions and beneficiaries of interest*

Land use and land management decisions, as well as factors such as climate change and invasive species, have the potential to affect the source and transport of many different types of water quality constituents or contaminants. Identifying the beneficiaries of interest and then working backwards to determine the appropriate biophysical parameters that have the greatest potential to affect those groups provides focus for research efforts and can ensure that subsequent work captures the most important drivers and ecosystem service consequences. Alternatively, if water quality information is available from previous monitoring or modeling, then the template can be used to identify all of the potential services affected by a change in a given nutrient or pollutant. One goal of the template is to draw attention to all of the constituents, endpoints, beneficiaries, and ecosystem goods and services related to changes in water quality. Therefore, an approach that considers both upstream drivers and downstream beneficiaries will generate the most comprehensive valuation.

2. *Identify shared inputs/outputs of biophysical and economic models*

After selecting the key actions and ecosystem service changes, the next step is to identify the inputs and outputs that need to be included in a set of integrated biophysical and economic models. In Figure 3 I use the term "valued attribute" to describe the aspect of water quality that can be measured or modeled in biophysical assessments and directly affects human well-being. For the service of clean drinking water, the valued attribute is the concentration of the nutrient or contaminant where increased health risks are associated with increased exposure to nitrate or toxins. For other services, an additional biophysical model may be needed to translate the driver of water quality change into the valued attribute. For example, stream temperature has been identified as a principal driver of the distribution and abundance of trout (Isaak and Hubert 2004, Railsback and Rose 1999). Here, a functional relationship is needed to translate changes in stream temperature into changes in either the size and abundance of trout populations or the area of suitable habitat for each species. As noted by Eaton and Scheller (1996), warming water temperatures may also alter species composition, shifting angling value from cold-water species to warm-water species. In some cases, there may be alternative choices of the valued attribute and what should be chosen depends on biophysical understanding, links to human well-being, and data availability.

3. Select appropriate biophysical models

Applying the framework requires the user to identify an appropriate biophysical model to capture the effects of an action on the valued attribute at the defined endpoint. The ecosystem services model InVEST estimates how changing land use or management resulting from alternative policies or future scenarios will affect nitrogen and phosphorus retention (Tallis et al. 2011). To use this model in my framework, nutrient outputs need to be linked to a valued attribute from Figure 3, such as changes in lake water clarity. Comprehensive valuation of water quality may require different biophysical models for each water quality constituent. For example, a groundwater model could be employed for services associated with nitrate contamination of drinking water wells and a river basin water quality model could be used to route nutrients downstream to predict consequences for coastal regions. Differing spatial and temporal lags for each service mean it is important to consider how the concentration of any given constituent changes across space and through time (Davenport et al. 2010).

4. Select appropriate economic models

In addition to identifying an appropriate biophysical model, applying the framework requires linking valued attributes at particular endpoints with economic models that measure the value of these attributes to specific beneficiaries. For example, changes in the concentration of nitrate in groundwater affect human well-being where wells supply drinking water to residents. Economic models can be used to compare the well-being of people prior to and after a change in water quality. These models predict how changes in nitrate concentrations at drinking water sources will affect behavior, such as prompting the installation of treatment systems by municipal water treatment facilities or the purchase of bottled water by well owners. While these costs can be used as proxies for economic values, it is important to distinguish the costs incurred through avoidance activities (the price of a new treatment system) from the true value associated with access to clean drinking water (difficult to measure, but likely of much greater value).

Economic models should measure change in value in terms of a common monetary metric. Where the valued attribute is a market good such as fish or shellfish, valuation is fairly straightforward. However, most water quality-related ecosystem services are not directly associated with market goods, so values must be estimated using non-market valuation techniques. Both market and non-market values are context dependent; they are influenced by the physical, economic, and regulatory settings in which the valuation takes place as well as on social or cultural norms. For example, the amount that a user is willing to pay to engage in a recreational activity such as swimming varies by income level as well as by the availability of substitute recreational opportunities (Haab and Hicks 1997). There is also variability in perceptions of the way water quality affects the suitability or desirability of recreation in different locations. Surveys of water recreationists in Minnesota, for example, have found that the level of lake water clarity users rate as "suitable for swimming" ranges from just 0.5 meters to at least 2.0 meters depending on the baseline water quality of the region (Heiskary and Walker 1988).

5. *Consider existing models and data sources*

While there are few examples of integrated, comprehensive analyses of ecosystem services related to water quality, there is a wealth of useful information with which to build such an assessment. I have assembled a comprehensive literature review of water quality valuation studies, added relevant biophysical models and case studies, and linked these references to each row in the valuation template presented in Figure 3 (Appendix 1.1). In some cases, existing work is sufficient to translate biophysical outputs to changes in service provision and value. However, few generalizable models linking actions to changes in value exist for water quality-related services. In many instances, researchers will have to collect new data in their region of interest or make assumptions about how to adapt existing models developed in other contexts. Recent work has advanced the practice of value transfer by developing valuation relationships that can be parameterized by the user with local data (e.g. Johnston et al. 2005, Patanayak et al. 2007).

Discussion

There are many challenges associated with implementing an integrated modeling approach that links actions to changes in the values of water quality-related services. Current understanding of the biophysical dynamics that link actions to changes in valued attributes is incomplete at best, and there is also uncertainty surrounding economic value estimates for changes in environmental amenities. Despite these challenges, decision-makers are still called upon to make decisions about land use and resource management. Below I highlight biophysical and economic uncertainties related to water quality valuation and then describe how my framework can help to identify and address these challenges.

Challenges linking changes in water quality to changes in human well-being

There are some services, such as the effects of increased nutrient loading on commercial fish and shellfish productivity, where uncertainties in the biophysical relationships make it difficult to reliably model changes in the valued attribute. In coastal areas, nitrogen loading has been linked with the spatial extent and intensity of hypoxia, shifting the timing of commercial fishing seasons and altering the size distribution of catches (O'Connor and Whitall 2007, Diaz and Rosenberg 2011). Quantifying the effects of nitrogen loading on commercial fishing is difficult because other stressors such as over-fishing and climate change also affect fish populations (Breitburg et al. 2009). Furthermore, improving water quality in ways that increase fishery productivity may generate little net benefits if the fishery itself is poorly managed (Freeman 1991). With the exception of a few well-studied systems (Huang and Smith 2011), there are no generalizable models that predict how a change in nutrient loading will affect fish or shellfish harvesting. Similar limitations apply to the relationship between harmful algal blooms and nutrient loading to coastal systems (Heisler et al. 2008). There are documented statistical relationships between nutrient loading and harmful algal blooms (Anderson et al. 2002, Beman et al. 2005). However, other physical and biological mechanisms likely modify responses to nutrient loadings (Heisler et al. 2008). In addition, there is no consensus on how to model changes in the recreation or commercial values based on the frequency, toxicity, extent, or duration of a harmful bloom. Lack of ability to tie actions to changes in ecosystems and to changes in valued attributes is a major limitation in assessing a number of ecosystem services.

Challenges linking changes in ecosystem goods and services to changes in value

In some cases, biophysical relationships are well understood but the economic tools used to link biophysical changes to human well-being are not generalizable or are not straightforward in their application or interpretation. Required inputs for predictive economic models vary depending on the ecosystem service measured (recreation vs. a marketed good such as fish), but common inputs include information on income, population, distance between users and resources valued (e.g.

lakes) in addition to water quality metrics. One common limitation of economic models that estimate changes in recreational value associated with changing water quality is that water quality inputs to the model are in the form of subjective water quality scales in lieu of quantitative biophysical metrics. These model inputs commonly take the form of compound metrics that combine several variables in a water quality index (e.g. Bockstael et al. 1989), use descriptive terms such as swimmable, fishable, or boatable to characterize water quality (e.g. Carson and Mitchell 1993, Van Houtven et al. 2007), or stated preference surveys where respondents rate water quality on a five point scale (e.g. Lipton 2004). While widely used, these approaches provide no clear link between biophysical data on water quality and the qualitative scale used in the economic study. Descriptive indices can also make it difficult to generalize model results across different geographical regions or demographic groups where there is variation in public perceptions of what constitutes clean water (Heiskary and Walker 1988).

Finally, there are non-use values such as the intrinsic value of intact food webs or the cultural values associated with the existence of species or habitats that are difficult to quantify using economic tools. Some estimates suggest these non-use values make up a significant portion of total value (Brown 1993, Johnston 2009). However, apart from stated preference surveys there are limited economic approaches to approximate these values which are likely to be highly contextual and localized.

Even for situations where there is robust biophysical and economic data, valuation following the framework is time-consuming and requires careful consideration of modeling assumptions and the propagation of uncertainty throughout the pathway from action to value. Still, the framework represents an improvement over existing “total value” approaches to ecosystem service valuation that tend to mask potential sources of uncertainty and make it difficult to assess confidence bounds on estimates of value. Using my template, researchers can identify exactly where uncertainty might be greatest and conduct sensitivity analyses to explore the effects of uncertainty on valuation estimates all along the pathway from action to change in value. This allows for transparent explanations of sources of uncertainty and can identify key gaps for future research investment. Our approach also allows users to track the distributional consequences of actions by identifying the unique sources of value that accrue to various individuals or groups of beneficiaries.

Examples of integrated models for water quality valuation

There are a few examples of integrated biophysical and economic models for the valuation of water quality that fit the proposed framework and can serve as models for future work. Egan et al. (2009) coupled water quality monitoring data from lakes across Iowa with survey data on household characteristics and trip information to develop a recreational demand model that predicts lake usage and willingness to pay as a function of changing water clarity. Huang and Smith (Huang and Smith 2011) developed a spatially-explicit bioeconomic model that predicts how changing levels of nitrogen pollution affect the ecological drivers of hypoxia. They linked this biophysical model with an economic model of the commercial blue crab fishery in the Nuese River Estuary. Their work was used to predict how changes in nutrient loading in the watershed could affect fishery rents in the estuary. These two examples demonstrate that valuation of water quality is both robust and feasible when ecological and economic relationships are considered simultaneously in model development and parameterization. Neither model was meant to be generalizable to other regions or applications, but with additional research there is potential to build more integrated models such as these and create new models for improved benefits transfer following the valuation template.

Future work on water quality valuation should begin by improving integration of existing models where there is general agreement on the valued attribute and endpoint. Biophysical models of changing water quality can be fed into economic tools listed in Figure 3 to estimate the net present values of modeled changes in water quality. Ideally, information is needed not just on current values, but on changes in the stream of benefits into the future. Doing so would allow researchers to use dynamic optimization approaches to identify the set of action that would maximize the value of water quality-related services over time.

Conclusion

Managers are under increasing pressure to adopt practices to reduce the negative consequences of agriculture, grazing, timber harvesting, and other management practices on water quality. Information on the value of water quality improvements is needed to evaluate the return on investment in conservation practices as well as to inform policies or payment programs that compensate land owners for benefits generated by their actions. Water quality assessments would be more meaningful to the public if modeled changes were presented not just as concentrations of nitrogen or phosphorus, but also in terms of risks to drinking water contamination, reduced fish and shellfish catches, or diminished recreational opportunities. To date there has been a lack of methods to inform decision-makers on how their actions would affect these valuable services.

I have addressed this gap by introducing a generalizable framework for the assessment and valuation of water quality services. This work is the first to describe the multiple biophysical and economic pathways that link actions to changes in water quality-related ecosystem goods and services. Our template overcomes many of the shortcomings of existing approaches by integrating biophysical and economic models, basing value estimates on marginal changes in service provision, and accounting for multiple sources of value without double-counting.

Information on the provision and value of ecosystem services is increasingly informing payment for ecosystem services schemes and ecosystem service markets across the globe (Kinzig et al. 2011). Decisions such as weighing the relative consequences of agricultural extensification vs. intensification are highly sensitive to the value placed on water quality changes. It is critical that water quality-related services are not left out of research that informs these new markets and decisions. Our framework allows researchers to improve decision-making now by using existing models and data presented in the valuation template, while also encouraging future research that targets gaps in our understanding of the biophysical and economic drivers of changes in water quality-related values.

Chapter Two

Land-use change and costs to water quality: A case study in groundwater nitrate contamination in southeastern Minnesota

Loss of grassland from conversion to agriculture threatens water quality and other valuable ecosystem services. Here I use a logistic regression approach to estimate how land-use change affects the probability of groundwater contamination by nitrate in private drinking water wells. I found that recent (2007 to 2012) grassland loss to agriculture in southeastern Minnesota is expected to increase the future number of wells exceeding 10 ppm nitrate-nitrogen by 45% (from 888 to 1,292 wells). I link outputs of the groundwater well contamination model to cost estimates for well remediation, well replacement, and avoidance behaviors to estimate the potential economic value lost due to nitrate contamination from land-use change. I estimate $2.8 to 12.2 million in costs over 20 years to address the increased risk of nitrate contamination of wells. My approach demonstrates how biophysical and economic models can be integrated to estimate the ecosystem service consequences of land-use change.

Introduction

Largely due to rising commodity prices, grass-dominated land covers are being converted to annual row crops such as corn and soybeans across the Midwestern U.S. (Johnston 2013, Wright and Wimberly 2013). The consequences of cropland expansion include declines in habitat for game and non-game wildlife, declines in soil carbon storage, and increased risk of soil erosion (Euliss et al. 2010, Stephens et al. 2008, Culman et al. 2010, Smith and Searchinger 2012, Faber et al. 2012). Grassland conversion to row-crop agricultural can also negatively affect water quality through the increased export of nutrients, sediment, and other agricultural chemicals (Donner and Kucharik 2008, Secchi et al. 2011, Wu and Liu 2012). These changes in water quality may affect multiple water quality-related ecosystem goods and services including recreation value, property values, human health, and other aspects of wellbeing (Keeler et al. 2012).

The link between land-use change, changes in water quality, and impacts to people requires integrating biophysical models sensitive to land use change with economic approaches that assess the welfare consequences of changing levels of valued goods and services. Establishing these links is required for cost-benefit studies and ecosystem services assessments, both of which are in increasing demand to support policy evaluation and decision-making. Especially with respect to water quality changes, the links between declines in water quality and negative effects on human wellbeing are assumed, but rarely quantified (Dodds et al. 2008, Griffiths et al. 2012).

In this study, I explore the link between land-use change and changes in water quality in eleven counties in Southeastern Minnesota (SE MN), a region with high rates of observed grassland conversion to agriculture. While there are many ecosystem services that are directly or indirectly affected by changes in water quality (Keeler et al. 2012), I focus on what I believe to be the water quality-related service most sensitive to observed changes in land use and with the greatest potential threat to human wellbeing: the contamination of private drinking water wells by nitrate. The study region is characterized by high hydrologic connectivity between surface and groundwater due to the karst features that occur throughout SE MN (Alexander and Lively 1995, Tipping et al. 2001). Statewide groundwater vulnerability maps rank much of the region in the "high" or "highest" vulnerability classification to contamination (Porcher 1989). This suggests that groundwater aquifers in the region are sensitive to changes occurring on the land surface. In addition to vulnerability in the supply of clean groundwater, there is also high demand for groundwater resources in this part of the state. The eleven counties that make up SE MN support a population of over 700,000 residents, the majority of which rely on groundwater for their primary drinking water source (MPCA 2013).

I focus my analysis on nitrate because it is one of the most widespread contaminants in groundwater systems and one of the primary components of fertilizer applied to croplands (MPCA 2013, Nolan et al. 2002). Nitrate is highly soluble and mobile in soil, which facilitates leaching into surface and subsurface pathways (Vitousek et al. 1997, Tomer et al. 2010). Nitrate contamination also represents a public health concern. The US Environmental Protection Agency has set a maximum contaminant level (MCL) of 10 mgL^{-1} (10 ppm) nitrate-nitrogen due to concerns over the link between consumption of high levels of nitrate and methemoglobinemia or Blue Baby Syndrome (Spalding and Exner 1993). Exposure to levels of nitrate below the federal drinking water standard (2.5 to 5.5 mgL^{-1} nitrate-N) has also been associated with increased risks of some cancers, birth defects, and spontaneous abortions (Weyer et al. 2008, Ward et al. 2000, Ward et al. 1996, Brender et al. 2013).

Previous studies on groundwater well contamination by nitrate have focused on screening for significant predictors of groundwater sensitivity to nitrate pollution (Burow et al. 2010), developing statistical models that link groundwater well contamination to well characteristics, nitrate sources, and transport and attenuation factors (Nolan et al. 2002, Wick et al. 2012a, Nolan and Hitt 2006, Lichtenberg and Shapiro 1997, Mair and El-Kadi 2013, Carbó et al. 2009), or studying consumer response to nitrate contamination and associated costs (Lewandowski et al. 2008). However, very few studies link all three components for a full cost accounting of land-use change impacts on groundwater contamination and economic value. These assessments are needed to evaluate the benefits of regulations such as the Clean Water Act, efficiently target conservation and restoration resources, design incentive or payment for ecosystem services schemes, and understand the human costs of environmental change (Daily et al. 2009, Iovanna and Griffiths 2006, Kinzig et al. 2011, Tallis and Polasky 2009)

This chapter addresses four questions related to assessing the water quality consequences of land-use change: 1) Which biophysical and hydro-geologic factors identify groundwater wells that are susceptible to contamination due to land use and land-use change? 2) For these "at-risk" wells, what is the relationship between surface nitrate loading and groundwater nitrate contamination? 3) Based on the modeled relationship between well contamination, surface nitrate loading and other variables, how many groundwater wells are likely to be at increased risk of contamination due to land-use change? 4) What are the societal costs associated with these modeled changes to groundwater quality?

Methods

My objective was to estimate nitrate contamination and associated costs for all recorded private drinking water wells in SE Minnesota. However, well chemistry data were only available for a subset (less than 30% of wells in the public record). Therefore, I first explored the relationship between well contamination by nitrate and likely explanatory variables affecting the source, transport, and attenuation of nitrate for a subset of wells with recent chemistry data and other known attributes. Second, I used these predictors to create a model that estimates the probability of well contamination. Third, I applied this model to all wells with spatial location information and data on significant predictors to estimate the expected number of contaminated wells under a baseline and cropland expansion scenario. Finally, costs associated with well contamination were applied to estimates of the number of wells at future risk of contamination due to land-use change.

Well dataset

The Minnesota Department of Health and the Minnesota Geologic Survey maintain the County Well Index (CWI), a spatially-explicit database of geologic and construction information from well logs for reported wells drilled in Minnesota since 1974. In the eleven county study region, there are 22,516 CWI wells with location information (located wells) and 16,126 wells without location information (unlocated wells) for a total of 38,642 wells. Of these wells, 8,864 wells have at least one recorded nitrate chemistry reading since 1950. Few wells have been tested consistently over time. Most wells have only been sampled once, and some wells have not been sampled in decades. In order to assess the influence of surface nutrient loading associated with recent land use in the region I narrowed the subset of wells to those with chemistry readings recorded over the last seven years. Previous studies linking land use and groundwater nitrate concentrations have found lag times of years to decades for the effects of land-use change to influence groundwater nitrate (Shilling and Spooner 2006, Tomer et al. 2010). For this reason, I include well chemistry data through the most recently recorded sampling dates (2012) and compare these readings to a baseline land use map for the year 2007 (NLCD Cropland Data Layer).

The spatial distribution of wells with nitrate data and the location of all CWI wells are shown in Figure 1. I calculated the maximum concentration of nitrate recorded over the seven year period for each well. I selected the maximum value (as opposed to the mean concentration) because the federal standard or maximum contaminant level (MCL) for nitrate of 10 mg/L (as nitrogen) represents the highest level allowed in drinking water. The MCL for nitrate is a legally-enforceable standard for public water suppliers regulated by the EPA. Private well owners are not required to abide by these MCL standards, but I make the assumption that well owners will treat or avoid water that violates federal guidelines.

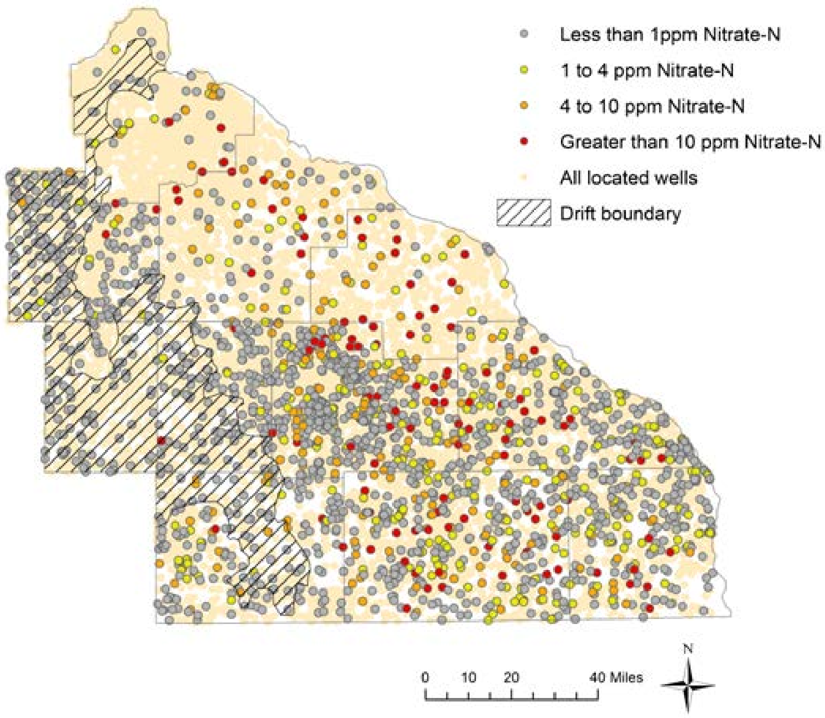


Figure 1. Spatial location of all located wells and wells with recent chemistry data. The shaded polygon represents the eastern boundary of glacial drift deposits where the depth to bedrock is greater than 50 ft. I tested the maximum nitrate concentration data for spatial autocorrelation using Moran's I and found no evidence for significant spatial clustering (z = 1.51, p = 0.12).

Explanatory variables

I assembled a set of explanatory variables previously identified as important in explaining variation in well contamination by nitrate (see Appendix 2.1). Nitrate contamination of groundwater is related to factors that affect the source of nitrate inputs, factors that affect the transport or downward movement of nitrate into groundwater, and attenuation factors that relate to the potential for denitrification as nitrate moves through the subsurface into groundwater. Transport factors include the presence of confining layers that prevent downward movement of water, and soil characteristics that can reduce permeability and subsurface drainage. Attenuation factors include the presence of organic matter, dissolved oxygen concentrations in aquifers, poorly drained soil, and other factors that would lead to low oxygen conditions that facilitate the denitrification of nitrate and hence reduce the quantity of leached N that reaches groundwater (Kellogg et al. 2010, MPCA 2013). I did not have information on hydraulic gradients or sub-surface lateral flow pathways so the model parameters only address factors related to the vertical transport of nitrate.

Depth is also an important predictor of groundwater nitrate contamination. Shallow wells and wells tapping aquifers with fewer overlying layers of bedrock are more likely to be affected by changes in contaminant loading at the surface (Burow et al. 2010, Gurdak and Qi 2012, Lichtenberg and Shapiro 1997, Nolan and Hitt 2006, Gardner and Vogel 2005, Tesoriero et al. 2004, Runkel et al. 2013). For each well, I estimated the vertical rank as the number of geologic formations above the tapped aquifer, counting down from the uppermost bedrock unit (Figure 2). Aquifer rank below surficial bedrock was found to be significant in previous studies on groundwater contamination in the region (Mubarak 2003, Harkanpar 2008).

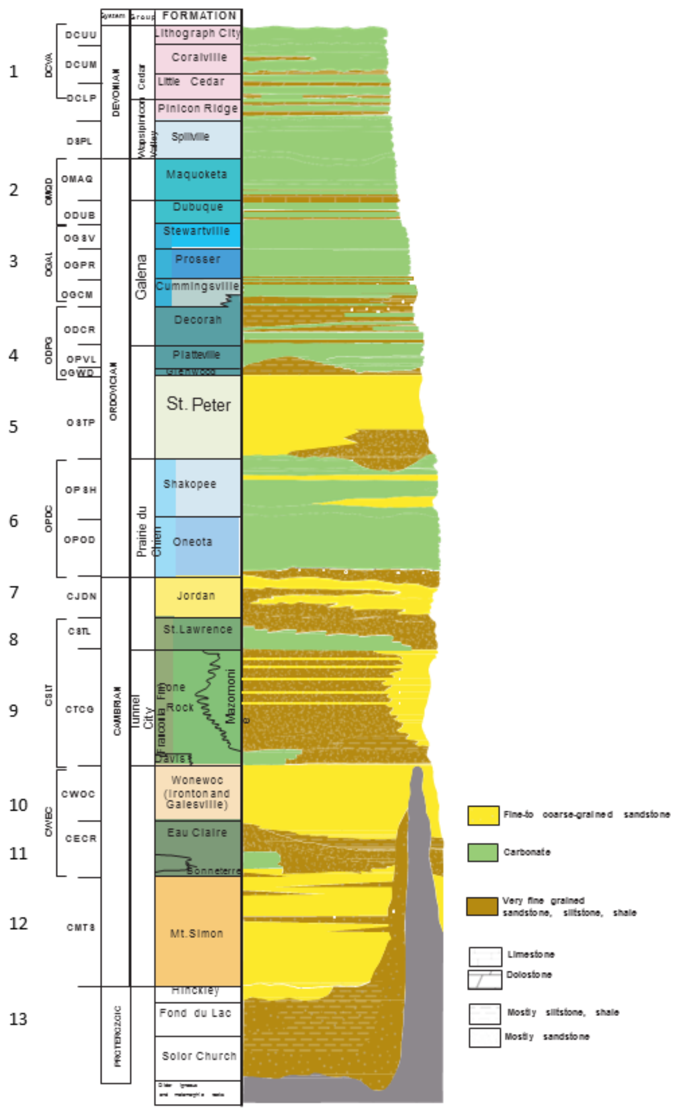


Figure 2: Stratigraphic column for bedrock of southeastern Minnesota. Numbers indicate the vertical rank of each formation. Numbers were assigned to each well based on the aquifer identified in the driller's records. I

then estimate the difference between the rank of the uppermost (surface) bedrock at each well site (from surficial geology maps) and the rank of the tapped aquifer (aquifer rank variable). Cross-section modified from Mossler (2008) and Runkel et al. (2013).

Similar to previous studies, I assigned soil characteristics and surface nitrate loading values to each well based on an estimated 500 m recharge zone around each well point (Nolan and Hitt 2006, Nolan et al. 2002). I evaluated other radii but found the most significant relationship between land use and well nitrate at 500 m. I generated 500 m buffers around each well in ArcGIS and then used spatial joins and zonal statistics to assign surface nitrate load, geologic attributes, and soil characteristics to each well (Table 1). I acknowledge that the surface buffer for each well only captures vertical flow of water from the region above each well and does not explicitly address lateral flow paths, residence time, or aquifer volume, all of which may be important in predicting groundwater well contamination.

Table 1. Variables used in fitting the nitrate contamination model. In addition to the continuous variables listed here I also investigated the significance of nominal variables for surficial geology type, bedrock geology unit, presence of confining layers (aquitards), presence of grout in well construction, and aquifer type in predicting nitrate contamination. Soils data were obtained from the USDA Natural Resources Conservation Service (NRCS) Soil Survey Geography database (SSURGO). Unless otherwise noted, the soils data are based on the dominant component for all known layers (0-999 m).

Explanatory variables considered in model selection	**Max**	**Min**	**Mean**	**SD**	**Source**
Sum of the surface load of nitrate-N around each well based on 2007 land use land cover (kg nitrate-N/ha/yr)	11,429	315	2,906	2,158	See Appendix 2.3
Aquifer rank below the uppermost bedrock unit	6	0	1.7	1.3	See Fig. 3
Well depth (m)	850	11	283	144	County well index
Drift thickness and permeability (scale 1-3, with 3 being most permeable)	2.97	0.95	1.60	0.34	Minnesota Geologic Survey (categorical variable representing relative permeability of unconsolidated sediments)
Average percent clay in well recharge zone	38.40	0.02	20.13	4.65	NRCS SSURGO
Average percent organic matter in well recharge zone	21.38	0.01	1.27	0.95	NRCS SSURGO
Average percent sand in well recharge zone	90.50	0.11	28.72	15.99	NRCS SSURGO
Average drainage class in well recharge zone	6.61	1	4.40	0.81	NRCS SSURGO
Average soil water content in well recharge zone	433.3	24.1	238.8	57.4	NRCS SSURGO
Percent of pixels in well recharge zone classified as "well drained" (soil hydric groups A and B)	100	0	60.0	26.0	NRCS SSURGO

To estimate the annual average load of nitrate to the recharge zone around each well under each scenario, I used land use-specific nitrate export coefficients. For the baseline land-use scenario I used a reclassified version of the 2007 Cropland Data Layer produced by the U.S. Department of

Agriculture to define the extent and spatial pattern of land use around each well (See Appendix 2.2 for reclassification scheme). Export coefficients for each major land cover or crop type were estimated from a literature review (See Appendix 2.3 for export coefficients) and represent the nitrate available for leaching through surface or subsurface pathways due to inputs from crop residues, fertilizers, and atmospheric deposition (Reckhow and Simpson 1980). Where possible, nitrate export values were adapted from field studies in similar soil and climatic conditions. For example, values for corn represent annual export of nitrate observed in Minnesota watersheds with representative drainage, fertilizer use, and tillage (Appendix 2.3). The export coefficients used in this analysis were developed for a watershed water quality model for the study region and calibrated so that the annual water yield and nitrate export matched observed annual average values at the watershed outlet averaged across all surface and sub-surface flow paths (Keeler et al. *in prep*). This approach differs from previous groundwater models which use proxies for nutrient load such as the percentage of agricultural or developed land, or counts of the number of septic systems or number of confined livestock operations in a well recharge zone (Nolan et al. 2002, Gardner and Vogel 2005, Wick et al. 2012b, Gurdak and Qi 2012, Liu et al. 2005). My metric for nitrate load is likely to better approximate true nitrate load to the surface because values are adapted from field studies under similar conditions and calibrated to observed data.

Model form and estimation

I constructed multiple logistic regression models for binomial response variables representing wells that exceeded 4 mg nitrate-N L^{-1} (4 ppm) and wells that exceeded 10 mg nitrate-NL^{-1} (10 ppm). I selected a 4 ppm nitrate threshold because exposure at or near to this level of elevated nitrate has been linked to birth defects and increased risks of some cancers (Weyer et al. 2008, Ward et al. 2000, Brender et al. 2013). The threshold of 10 ppm represents the maximum contaminant standard set by the U.S. Environmental Protection Agency (U.S. EPA 2011).

Logistic regression predicts the probability that a sample falls within a given response category and does not require the response variable to be normally distributed (well nitrate concentration is highly skewed due to the significant number of non-detects). Logistic regression has been applied in many previous studies on groundwater nitrate contamination, most commonly using a contamination threshold of 1-3 ppm to identify wells that exceed background or naturally-occurring levels of nitrate (Tesoriero et al. 2004, Gardner and Vogel 2005, Tesoriero and Voss 1997, Liu et al. 2005, Gurdak and Qi 2012).

In logistic regression, the mean response at any level of input is the probability of being in a category (above or below a threshold), where

$$\mathrm{P} = \frac{e^{(b_0 + bx)}}{1 + e^{(b_0+bx)}}$$

and P is the probability of exceeding a given threshold, b_o is a constant and *bx* is the vector of slope coefficients and explanatory variables. In order to transform the probability function so that a linear function can be fitted to the explanatory variables a logit transformation is applied. The logit function is

$$\ln\left(\frac{\mathrm{p}}{1-\mathrm{p}}\right) = \mathrm{b_o} + \mathrm{bx}$$

With this transformation, the logit is linearly related to the model parameters and standard linear regression tools can be used to estimate values for b_o and *bx*. Explanatory variables are fit to the logit function and then converted back into probability units.

Screening model variables for significance

For the subset of wells with recent chemistry data I screened all candidate explanatory variables for significance in a logistic regression model based on the 4 ppm and 10 ppm thresholds. The nominal variable representing the boundary of thick unconsolidated glacial deposits or drift was significant in classifying contaminated and un-contaminated wells. The drift boundary marks a region where the depth to bedrock is greater than fifty feet, compared to the bedrock-dominated eastern region where drift is thin and patchy (Figure 1). Only nine wells located within the boundary of glacial drift had nitrate concentrations greater than 4 ppm (or 2% of all wells in the drift zone), whereas 16% of all wells outside the zone of glacial drift had nitrate levels above 4 ppm. Due to the observation that wells within the drift boundary appear to be fairly well protected from nitrate contamination I removed these wells from the sample set based on the conservative assumption that these wells are less sensitive to changes in land use and corresponding surface loading of nitrate.

I used backwards stepwise regression using the minimum Akaike information criterion (AIC) and minimum Bayesian information criterion (BIC) to screen predictors for significance in JMP Pro 10 (SAS Institute Inc.). Additionally, I used the "best glm" (general linearized model) package in the statistical software package R which uses a cross-validation approach to identify significant explanatory variables and parameter estimates. In a cross-validation approach, subsets of data are excluded as test sets, models and significant parameters are estimated based on training sets, and then adjusted based on performance relative to the test sets.

Results of variable screening

There was almost perfect agreement between the stepwise AIC, stepwise BIC, and cross-validation approaches for identifying significant predictors. There was also general agreement across the two contamination thresholds, with the only exception being the explanatory variable percent organic matter, which was significant for only the 4ppm threshold model (Table 2). The other four significant predictors of groundwater well nitrate concentration were surface load of nitrate in a well recharge zone, percent clay in a well recharge zone, mean drainage class in a well recharge zone, and aquifer rank (Table 2).

Table 2: Parameter estimates and significance tests for the 4ppm and 10ppm logistic regression models

			Effect Likelihood Ratio Tests	
	Estimate	Standard Error	Logistic Regression ChiSquare	Prob> ChiSquare
4 ppm response variable where 1 = threshold exceeded				
Intercept	-7.000	0.835		
Sum of the surface load of nitrate-N around each well (kg nitrate-N/ha/yr)	0.0003	3.59e-5	51.43	<0.0001
Average percent clay in well recharge zone	0.086	0.018	24.23	<0.0001
Average percent organic matter in well recharge zone	-0.577	0.205	11.52	0.0050
Average drainage class in well recharge zone	0.987	0.134	64.94	<0.0001
Aquifer rank below the uppermost bedrock unit	-0.810	0.073	151.18	<0.0001
10 ppm response variable where 1 = threshold exceeded				
Intercept	-14.538	1.409		
Sum of the surface load of nitrate-N around each well (kg nitrate-N/ha/yr)	0.003	0.00005	46.14	<0.0001
Aquifer rank below the uppermost bedrock unit	-1.103	0.126	107.39	<0.0001

Average percent clay in well recharge zone	0.166	0.031	35.10	<0.0001
Average percent organic matter in well recharge zone	ns	Ns	ns	ns
Average drainage class in well recharge zone	1.845	0.229	98.80	<0.0001

The significance of surface nitrate load in predicting groundwater contamination indicates that wells in the subset are sensitive to changes in surface nitrate loading and thereby sensitive to changes in land use and land management in the region. Wells with higher estimated surface loads had higher nitrate concentrations and greater probabilities of exceeding well contamination thresholds. Percent organic matter was negatively related to well contamination which may reflect increased rates of dentrification associated with soils with higher organic matter. I expected percent clay to also be negatively related to well nitrate due to inhibition in vertical transport of nitrate through the soil surface (Nolan and Hitt 2006, Gurdak and Qi 2012). However, I found the opposite relationship suggesting either clay content is correlated with another unknown factor or high clay content soils are managed in a way that increases vertical transport of nitrate to groundwater. Drainage class, a soil attribute derived from the Soil Survey Geographic Database (SSURGO) ranks soils from very poorly drained to excessively drained. As mean drainage class increased, nitrate contamination also increased which could be related to greater vertical transport of nitrate through well-drained soils (greater drainage = greater nitrate) and/or related to enhanced denitrification of nitrate in poorly drained soils (poor drainage = less nitrate). Aquifer rank was negatively related to nitrate contamination such that shallower aquifers (lower rank) were associated with higher nitrate wells (Figure 2).

Another way to interpret the effect of an explanatory variable using logistic regression is through odds ratios or $\frac{p}{1 - p}$ where p is the probability of exceeding the threshold value (4 ppm or 10 ppm). If a well is equally likely to fall into either the contaminated or uncontaminated categories (p = 0.5), then the odds ratio is 1. When the estimated probability of contamination is greater than .5, the odds ratio is positive and represents how many times more likely a well is to be contaminated versus uncontaminated as the value of an explanatory variable changes. The odds ratios for the explanatory variable of surface nitrate load are presented in Table 3.

Table 3: The range odds ratios for the explanatory variable surface nitrate load. Upper and lower 95% confidence intervals are in parenthesis.

	Range Odds Ratios 4ppm	Range Odds Ratios 10ppm
Sum of the surface load of nitrate-N around each well (kg nitrate-N/ha/yr)	17.5 (8.0 - 38.4)	45.8 (15.4 - 138.8)

The positive range odds ratio for surface nitrate load indicates that as nitrate load increases from the lowest recorded level to the highest recorded level, wells are 18 times more likely to exceed 4 ppm nitrate or 46 times more likely to exceed a 10 ppm nitrate threshold.

Adjusting the probability cutoff used to assign wells to categories

To estimate the number of contaminated wells, I translated the continuous logistic regression model outputs in probability units into a contamination prediction for each well. To do this, I needed to select the probability threshold to use in assigning wells to each response category (contaminated or uncontaminated) that both minimizes total error and comes closest to estimating the correct frequency of positive response events without overestimating contamination. A description of the probability threshold selection process is included in Appendix 2.5. In short, I selected probability cutoffs of 0.28 for the 4 ppm model and 0.24 for the 10 ppm model because they minimized the total number of misclassifications (false positives and false negatives) while coming closest to a" true" prediction of the total number of contaminated wells without overestimating contamination (Figure in Appendix 2.5).

Results

Application of the model to wells without chemistry data

To answer the question of how well contamination may respond to observed changes in land use I applied the logistic regression model to wells in the eleven county region with location information. Of the 22,516 located wells 4,661 lacked aquifer characteristics needed to estimate the aquifer rank variable. An additional 2, 748 wells were located under the region of glacial drift and were also excluded, leaving 15,107 wells. I applied the logistic regression model to this larger set of wells under two land use scenarios. For the baseline land use scenario I used the same 2007 land cover map and corresponding nutrient export values used to estimate the logistic regression model. I estimated the number of wells exceeding each threshold for the training (subset with chemistry data) and full well dataset (Table 4). Under the baseline scenario, 6% of groundwater wells were estimated to exceed a 10ppm nitrate threshold and 18% to exceed a 4 ppm nitrate threshold (Table 4).

Table 4. Estimated number of wells exceeding each contamination threshold for the subset of wells with chemistry data (training set) and the full set of located wells under the baseline and agricultural expansion scenario. Percent of wells in each category relative to all wells are in parentheses.

	Training set under the baseline scenario	2007 Baseline scenario	2012 Agricultural expansion scenario	Increase in the number of wells predicted to be at risk of contamination due to land-use change
Estimated number of wells exceeding 4 ppm	245 (14%)	2779 (18%)	3,562 (24%)	783
Estimated number of wells exceeding 10 ppm	94 (5%)	888 (6%)	1,292 (9%)	404
Total number of wells	1777	15,856	15,856	

Next I estimated risk of contamination under a scenario of agricultural expansion. The agricultural expansion scenario is based on the 2012 Cropland Data Layer using the same reclassification scheme used in the baseline 2007 land cover map. According to the land-cover data, there was a 26% net loss in grass-dominated cover from the baseline 2007 landscape to the 2012 landscape for this study region. Corn and soybean acreage increased by 27% over the same period. These trends are similar to those observed in recent analyses of land cover change in the Midwest which have shown rapid and widespread loss of grasslands to row crop expansion (Johnston 2013, Wright and Wimberly 2013). Under the 2012 agricultural expansion scenario, the model estimated 3,562 wells at-risk of exceeding the 4 ppm threshold (a 28% increase) and 1,292 wells at-risk of exceeding the 10 ppm threshold (a 45% increase; Table 4, Figure 3). The residence time of water as it moves vertically down from the surface to each well is unknown, therefore I cannot assume that land-use trends observed in 2012 will be reflected in well contamination in the same year (Schilling and Spooner 2006, Tomer et al. 2010). Through the parameter screening, I have attempted to limit the analysis to wells where it is reasonable to assume that there is exchange between surface and groundwater over shorter time periods (months to years). However, the effects of nitrate contamination at the surface may persist for years or even decades later (Tomar and Burkart 2003, Sebilo et al. 2013). For this reason the agricultural expansion scenario should not be interpreted as an estimate of well contamination in the year 2012, but rather an estimate of potential future contamination attributable to the land use change trends observed in this region.

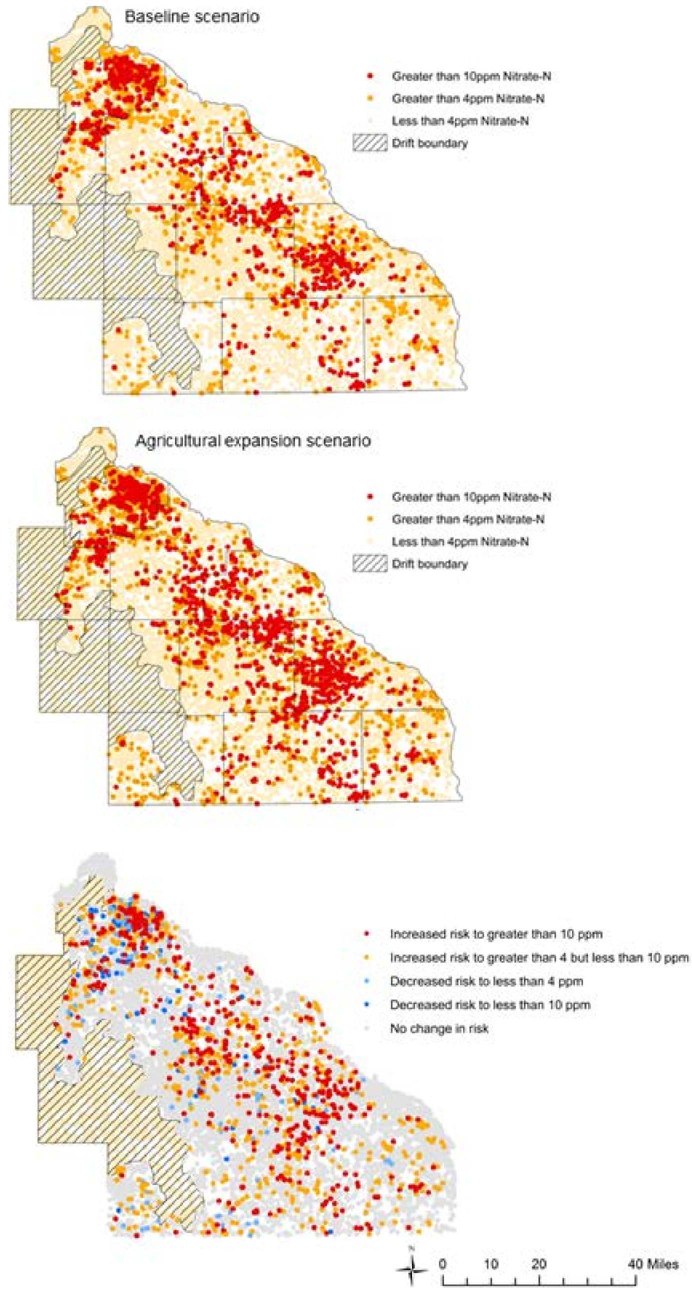


Figure 3: Model estimated risk to groundwater well contamination under the baseline and agricultural expansion scenarios. Bottom figure shows the estimated increase or decrease in risk of nitrate contamination for each well between the two scenarios.

Costs of modeled contamination

The costs of groundwater nitrate contamination include the costs of remediation actions taken to either replace a contaminated well, install a filtration system or other treatment technologies, or the costs of avoidance behaviors such as purchasing bottled water for drinking and cooking (Lewandowski et al. 2008; Table 5). If water is untreated and consumed then there may be costs related to potential health impacts from drinking untreated water with elevated nitrate (Townsend et al. 2003). The costs to an individual are dependent on their inherent risk for nitrate-related diseases and their responses to a perceived or unperceived threat to well water quality. For example, households with young children or pregnant mothers are at greater risk to methemoglobinemia and risks of birth defects or other prenatal conditions. Other sub-populations deemed to be at higher risk for nitrate-related cancers include adults with higher than median levels of red meat consumption (De Roos et al. 2003).

In a study of the costs of nitrate pollution in the European Union, van Grinsven et al. (2010) estimated that exposure to elevated nitrate in drinking water resulted in a loss in value equivalent to 1000 million euros annually due to increased incidences of nitrate-related colon cancer. The public health research linking elevated nitrate exposure below the drinking water standard (represented by the number of wells exceeding 4 ppm in the study) is still under debate (Powlson et al. 2008). I also lack data on household demographics that would allow us to assess well-specific household risk. Therefore I do not include health-related costs in my estimates. Instead, I focus on the costs associated with treating, replacing, or avoiding contaminated well water.

A 2008 study in Minnesota surveyed residents for actions taken if they perceived well contamination by nitrate (Lewandowski et al. 2008). The survey was conducted in conjunction with well nitrate testing so hypothetical responses to contamination could be compared to actual responses taken by owners with confirmed cases of nitrate contamination. Table 5 summarizes the costs associated with three nitrate treatment technologies, new well construction, and drinking bottled water to avoid exposure to elevated nitrate in home well water.

Table 5: Per household costs of responses to groundwater well contamination by nitrate. Low and high cost estimates are based on reported costs in Lewandowski et al. 2008, Mahler 2007 and estimates from regional well drillers. Bottled water costs assume two gallons daily per capita water consumption for a 2.2 person household at $0.33 to 1.22 per gallon (low, high bottled water cost estimates, respectively).

	Initial costs	Annual costs
Reverse osmosis	$300-1,300	$100-300
Distillation	$250-1,500	$400-500
Anion exchange	$600-2,200	$269-469
New well	$7,200-16,000	-
Bottled water	-	$529-1,959

I used the observed adoption rates reported by owners of contaminated wells from Lewandowski et al. (2008) to estimate the behavioral responses and estimated costs associated with modeled future risk to well contamination due to observed land-use change (Table 6).

Table 6: Costs associated with the modeled change in future well contamination due to land-use change. Adoption rates are from actual responses to well contamination in Minnesota from Lewandowski et al. (2008). Annualized costs are based on a 20 year time horizon for best estimate costs (high and low) for each potential response. Total costs represent costs over 20 years due to the number of additional predicted contaminated wells under the agricultural expansion scenario for each of the two contamination thresholds. Costs are greater if people respond to contamination at a 4ppm threshold.

	Adoption rate	Annualized costs per well	Total costs per well (20 year time horizon)	Total costs due to land-use change for a 4ppm threshold (783 wells)	Total costs due to land-use change for a 10ppm threshold (404 wells)
Nitrate treatment (weighted by adoption rates for each of the three technologies)	21.9%	$170-406	$3,394-8,119	$580,355-1,388,330	$298,662-714,462
New well	25%	$360-800	$7,200-16,000	$1,411,200-3,136,000	$727,200-1,616,000
Bottled water	25%	$529-1,959	$10,599-39,186	$2,077,522-7,680,534	$1,070,560-3,957,826
Do nothing	37.5%	-	-	-	-
Total Cost				**$4,069,077-12,204,864**	**$2,069,422-6,288,289**

The model predicts 783 additional wells are at-risk of exceeding 4ppm nitrate and 404 additional wells are at-risk of exceeding 10ppm nitrate due to land-use change in the region. The twenty year cost of this increased well contamination was estimated at $2.1-12.2 million depending on the threshold of contamination that triggers household action and cost assumptions for each response (Table 6). I assume the adoption rates of each potential action based on actual surveyed responses to elevated nitrate by private well owners in Minnesota (Lewandowski et al. 2008), which includes 37.5% of well owners doing nothing about their nitrate problem. If I assume that all households will treat for nitrate using the least-cost approach (installing a reverse-osmosis treatment system), then costs would be $0.9-2.9 million for treating all of the additional wells exceeding 10 ppm, or $1.8-5.7 million for treating all additional wells exceeding 4 ppm. Even though this scenario assumes all households will treat for nitrate (as opposed to only 62.5% of households based on actual responses) cost estimates for this scenario are lower because all households choose the lowest-cost approach. There may be other motivating factors besides cost that would influence a household decision to adopt a particular response as evident from the range of observed responses to nitrate contamination documented in Lewandowski et al. (2008).

These estimates also assume that all households are aware of the nitrate contamination. Previous surveys of nitrate contamination in groundwater wells showed that significant percentages of consumers are not aware of the nitrate levels in their wells. In the Minnesota survey of well owners, only 29% of respondents had tested their wells for nitrate within the last three years (Lewandowski et al. 2008). A study of nitrate contamination in California drinking water found greater than 50% of surveyed residents in areas with high nitrate water were not aware that nitrate was the source of contamination. The same study found that exposure to high nitrate water was concentrated in areas with low awareness of the problem and greater numbers of low-income households with fewer financial resources to deal with water contamination (Moore et al. 2011).

Cost estimates are likely to be underestimates as many wells in the region were excluded from the analysis because they were not in the well record, lacked specific location information (16,126 wells), or were missing data on explanatory variables (an additional 4,661 wells). Assuming these wells followed the same patterns observed for wells with location and attribute data, the total costs attributable to land use change would more than double. Finally, well remediation costs do not include health-related impacts due to consumption of elevated nitrate for those households that do not treat or avoid nitrate-contaminated water. These health-related costs are uncertain, but may exceed estimated treatment costs (van Grinsven et al. 2010, Sutton et al. 2011). Health impacts related to other agricultural contaminants in untreated private drinking water wells represent additional and additive costs (Gilliom 2007).

Discussion

The results of the logistic regression model identified surface nitrate load, percent clay, percent soil organic matter, drainage class, and aquifer rank as significant predictors of groundwater nitrate contamination in SE Minnesota. Surface nitrate loading was significantly related to land use change in the region, and the model applied to all located wells found observed land-use change increased the number of nitrate-contaminated wells. This result was consistent with previous studies that found a significant positive relationship between shallow aquifer concentrations of nitrate and the percent of agricultural lands in well recharge zones (Lichtenberg & Shapiro 1997, Tesoriero and Voss 1997, Nolan et al. 2002, Gardner and Vogel 2005, Liu et al. 2005, Nolan and Hitt 2006, Gurdak and Qi 2012, Wick et al. 2012, Mair et al. 2013).

Tests for model fit and predictability indicated good model performance but also highlight the challenges associated with predicting groundwater well contamination. In the absence of detailed information on subsurface geology, groundwater flow and transport models, spatially-explicit estimates of groundwater recharge, and information on aquifer volume and chemistry, it is difficult to accurately predict groundwater contamination over time and space. Factors considered in this study represent vertical transport pathways and processes that affect nitrate levels, but do not capture lateral movement of nitrate which can be especially important in Karst regions where groundwater flow paths are highly variable and difficult to estimate from surface characteristics (Runkel et al. 2003, 2013). Additionally, there are significant temporal lags in groundwater systems. It may take years or decades for the land-use related nitrogen inputs to affect groundwater nitrate concentrations in private wells (Tomer and Burkart 2003, Sebilo et al. 2013).

The potential future costs to private well owners due to the estimated increase in nitrate contamination from agricultural expansion were $2.1-12.2 million dollars over 20 years. These costs are conservative because a large number of wells were excluded from the analysis due to data availability. Cost estimates also do not include any health impacts associated with drinking untreated water for residents that are unaware of nitrate contamination or chose not to treat or avoid consuming contaminated water. While likely an underestimate of the total costs of well contamination in the region, groundwater remediation costs are unlikely to exceed the value of crop production due to agricultural expansion. A full cost accounting of the impacts of water quality changes in SE MN should include not only well remediation costs, but also human health impacts of drinking contaminated water (nitrate and other contaminants not considered here), costs to municipal water suppliers, recreational costs associated with eutrophication in regional lakes and rivers, lost property values due to algal blooms or degraded water quality, and costs associated with nutrient export to the Gulf of Mexico related to hypoxia. Three municipalities in the SE region are already responding to high nitrate levels in their public water supply (St. Charles, Lewiston, and Utica) and in Olmsted County the Galena aquifer and parts of the St. Peter and Prairie du Chien aquifers have been abandoned as sources of drinking water due to high nitrate levels (Terry Lee, Olmsted County Planning Department).

There are other drivers of change in the region that may exacerbate the negative water quality impacts of agricultural expansion. Groundwater extraction for irrigation, municipal water use, and water-intensive industries such as ethanol refineries and frack-sand mining are increasing demand on groundwater resources. As groundwater extraction increases it can change the hydraulic gradient and facilitate the draw-down of polluted water from upper aquifers. Grassland ecosystems in MN provide numerous other ecosystem services not considered in this paper that also generate significant public benefits threatened by increased rates of agricultural expansion (Noe et al. *in prep*, Stephens et al. 2008, Culman et al. 2010, Euliss et al. 2010, Faber et al. 2012).

In conclusion, this paper demonstrates the link between land use change, water quality changes, and impacts on human well-being following the interdisciplinary framework proposed by Keeler et al. (2012). The explanatory variables used in this analysis are widely available from state and federal geo-spatial databases and the approach outlined here could easily be applied to other regions. I find that land-use change will likely increase costs to hundreds of private well owners across southeastern Minnesota. These costs are in addition to the costs already born by well-owners due to baseline land use change in this predominantly agricultural region. While the costs may not exceed the value of the agricultural production, they may be useful in allocating resources to compensate affected individuals or to identify factors that could be incorporated into spatial decision support tools to target lands for conservation or best management practices designed to reduce groundwater contamination.

Chapter Three

Recreational demand for clean water: Evidence from geo-tagged photo visitation of lakes

More than 41,000 waters are listed as impaired by the U.S. Environmental Protection Agency under the Clean Water Act. Regulations designed to address these impairments can be costly, raising questions about the value of the public benefits that would result from additional investments in improving surface water quality. Cost benefit studies often rely on costly surveys or other detailed data collection about the study site, limiting the use of nonmarket valuation methods. Here I present an approach to assess the value of changes in water quality to lake recreation that offers the rigor of a revealed preference method, but can be executed with free and widely-available data. My approach uses geo-tagged photographs uploaded to the photo-sharing website flickr as a proxy for recreational visits to lakes. I find that improved lake water clarity is associated with greater lake photo-visitation and that lake users are willing to pay more to visit clearer lakes. I estimate a one-meter increase in lake water clarity in Minnesota and Iowa lakes is associated with $22 in increased willingness-to-pay per lake visitor and would generate 1,094 – 1,183 additional annual visits per lake. This study could be used to inform more efficient allocation of state resources to protect clean water by evaluating the potential benefits of addressing a growing list of aquatic impairments.

Introduction

Lakes, rivers, and streams provide many benefits to the general public, but these benefits are not well captured in markets. This is problematic because information on the value of water resources is needed to inform many policy and regulatory contexts. For example, the Environmental Protection Agency (US EPA) is required to estimate the benefits and costs associated with major rules and regulations designed to safeguard aquatic habitat (e.g. Federal Register Executive Order 12291; Feb. 17, 1981). Information is needed on the relationship between stressors such as pollution and consequences for ecosystem services like aquatic recreation and human health. Cost benefit assessments for water quality changes are also considered in the design of payment and incentive programs and in spatial planning decisions related to investments in conservation or habitat restoration (Olmstead 2010, Griffiths 2012).

Despite high demand for information on water quality values, estimates often fall short of the needs and expectations of decision-makers (Keeler et al. 2012). Valuation data is time-consuming and expensive to collect, existing value estimates are often not transferrable to other decision-contexts, and value estimates are not expressed in terms of marginal changes in stressors such as increased pollutant loads or land-use change. The previous chapter addressed this gap through an investigation of treatment costs and human health impacts associated with groundwater contamination. In this chapter, I contribute a second advancement in the science of ecosystem service valuation by developing a generalizable approach to assessing how a change in water quality affects the value of lake recreation.

Recreation is an important water quality-related service, especially in developed countries where it has shown to be one of the greatest contributors to the economic value of water quality (Dodds et al. 2009). While the biological effects of degraded water quality are well-studied, measuring the relationship between water quality changes and recreational value is challenging (Wilson and Carpenter 1999, Corrigan et al. 2007, Bateman et al. 2011, Doi et al. 2013). In a 2009 paper Dodds et al. estimated the lost recreational value from eutrophication in the U.S. at $0.4-1.2 billion per year. They arrived at this estimate by assuming lakes classified as hypereutrophic were closed for a defined number of days each year. The change in recreational value was equal to the value of the number of trips lost due to eutrophication. The value estimates produced by Dodds et al. have been used by subsequent ecosystem services assessments (Compton et al. 2011) and while they are Illustrative of the value of water, they do little to assist decision-makers in understanding the marginal value of a predicted or proposed change in water quality.

To arrive at a value of water quality where no market exists to determine a value, economists must use nonmarket tools. Stated preference approaches use surveys to ask how much respondents would be willing to pay for a stated improvement in water quality. For example, Matthews et al (2002) asked residents how much they would be willing to pay for a 40% reduction in phosphorus to the Minnesota River. Carson and Mitchell (1993) used a contingent valuation survey to evaluate the net benefits of the Clean Water Act, arriving at an estimate of $29.2 billion annually (in 1992 dollars). Stated preference surveys such as these are useful in eliciting both use and non-use values for water resources. However, the benefits estimates from stated preference approaches can be difficult to adapt to other contexts. The researcher must assume how to translate the stated value to proposed improvements in other environments for different levels of water quality changes.

Revealed preference approaches are an alternative to stated preference methods that infer values for non-market goods based on how people tradeoff private goods (time, money) in response to variation in the quality of a public good (Champ et al. 2003, Freeman 2003, Phaneuf and Smith 2005). Hedonic studies are a type of revealed preference approach where the value of water quality is determined from variation in property values. In a study of lakeshore property values in Minnesota, Steinnes (1992) found that a one foot increase in water clarity increases lakeshore land values by $206 per lot (in 1987 dollars). Other studies have also found a positive relationship between water clarity and property values (Boyle and Brochard 2003, Krysel et al. 2003, Michael et al. 1996).

A second revealed preference approach uses observations of the recreational choices made by users of recreational sites to estimate the value placed on water quality and other site attributes (Smith et al. 1986, Dumas et al. 2005). Travel cost estimates assume users have to pay increased mileage costs, user fees, and time as they travel greater distances. These travel costs serve as proxies for the market price of an environmental good or service (Bockstael et al. 1995). Using a travel cost approach, Egan et al. (2009) found that if water quality in all Iowa lakes improved to the level of the highest quality lake in the state it would generate an additional value of $150 per household per year ($180 million statewide). Travel cost studies from other regions have found similar trends with water quality improvements associated with greater value to lake, river, or beach recreation (Parsons and Kealy 1992, Bockstael et al. 1987, Phaneuf 2002, Van Houtven et al. 2007).

Similar to stated preference approaches, travel cost and hedonic studies have limitations. Collecting survey or site-specific data is expensive and time consuming and most decision-makers do not have the resources to conduct studies for each application where information on water quality values is needed (Bateman et al. 2011, Griffiths et al. 2012). Even in the state of Minnesota which places great value on aquatic habitats and resources and where information on the value of lake recreation is likely in high demand, the last survey on Minnesota lake recreation was completed over 20 years ago and only assessed angler trips to lakes (Feather et al. 1995).

In this study I propose an approach for estimating the value of changes in lake water quality using data from online social media that circumvents the need for survey data. This approach offers the same rigor as the revealed preference approaches based on hedonic models or travel cost studies, without relying on expensive or time-consuming data collection methods. Instead, I take advantage of the increase in spatially-explicit crowd-sourced content available online. These volunteered data are increasing in volume each year and allow researchers the opportunity to rapidly and inexpensively study user behavior and preferences over space and time (Li et al. 2013, Preis et al. 2013, Sun et al. 2013).

In this chapter, I use geo-tagged photographs uploaded to the photo-sharing website flickr as a proxy for surveyed lake visitation. I first test the method by comparing photo-visitation data with survey data for household trips to Iowa lakes. Next, I use multiple regression to evaluate which lake attributes and other factors best explain lake photo-visitation to Minnesota and Iowa lakes. I then apply the regression model to a scenario of increased water quality to evaluate the change in lake visitation and associated value to lake recreation.

Methods

Using data from geo-tagged photographs to estimate visitation is an approach first introduced by Wood et al. (2013). Wood et al. used photos uploaded to the photo-sharing website Flickr to estimate recreational visits to natural and cultural attractions around the world and found that photo-visitation is a reliable proxy for empirical visitation rates (Wood et al. 2013). To assess photo visitation at Minnesota and Iowa lakes, I queried Flickr for all photos taken within the boundaries of 3,055 lakes in Minnesota and 135 lakes in Iowa. I selected these states because of the availability of water quality data and surveyed lake visitation (for Iowa lakes) and because the region represents a gradient of water quality from relatively undisturbed oligotrophic lakes to lower-quality eutrophic lakes. Each lake was buffered to a distance of 30 meters to account for photos taken along the shoreline. This returned a total of 41,852 unique geo-tagged photos for Minnesota and Iowa lakes. For Minnesota, lake photos represent about 3% of all geo-tagged Flickr photos taken anywhere in the state over the same period.

For each lake that returned geo-tagged photos, I estimated the annual number of unique photo-user-days per lake which represents the number of unique combinations of users and lake destinations within a 24 hour period. For example, if an individual took multiple photos at the same lake in the same day, that lake would be assigned a single photo-user-day. Photo-user-days were averaged across the eight year period for which photos were downloaded (2005 to 2012). In Minnesota, 1079 lakes were visited and photographed by Flickr users and in Iowa, 72 lakes had geo-tagged Flickr photos (Figure 1).

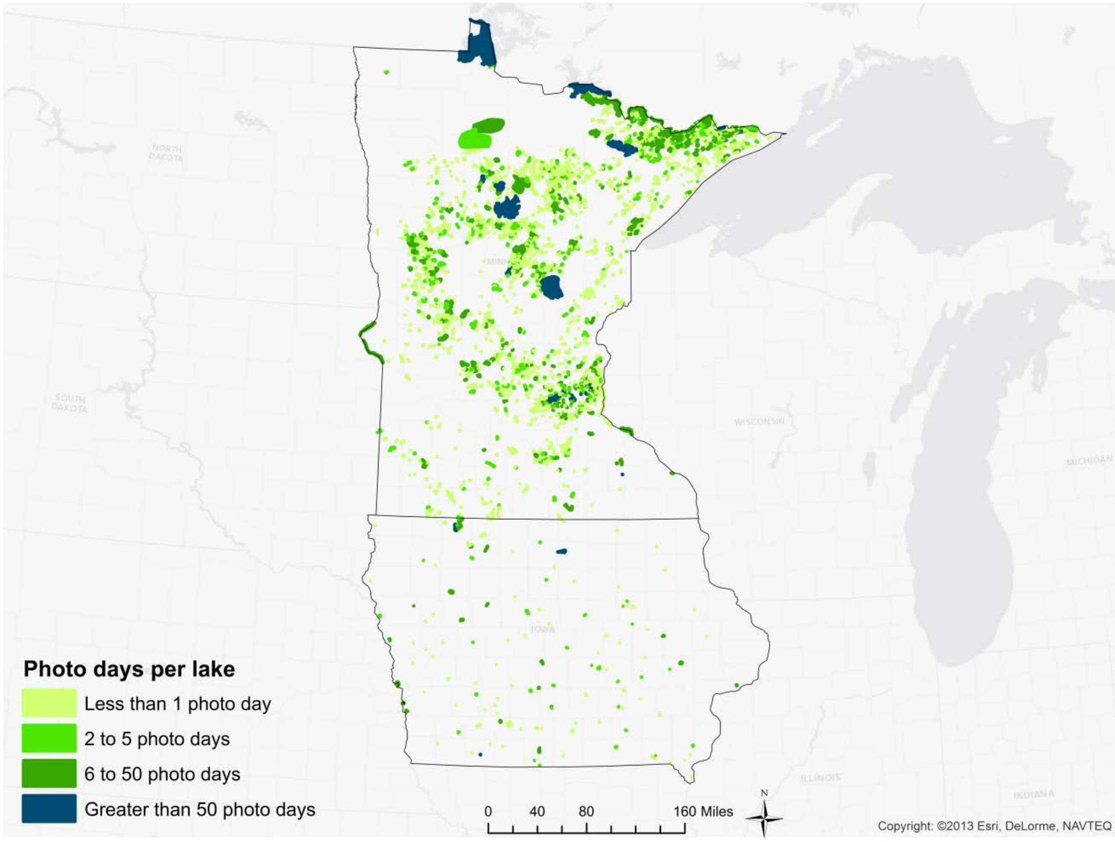


Figure 1: Distribution of photo visitation in Minnesota and Iowa lakes as measured by Flickr photos. Photo-days per lake represents the sum of all unique daily lake and user combinations uploaded to Flickr from 2005 to 2012. There was no evidence for spatial autocorrelation of photo days per lake based on Moran's I test (z = 1.12, p = 0.26)

In addition to the number of unique photo-visits I also downloaded the user profiles associated with individuals that uploaded lake photos. About 40% of Flickr-users with uploaded lake photos provided information in their online profile that revealed their home location. Flickr-visitors to Minnesota lakes came from 47 states and 36 countries, with 66% of visitors reporting a home location from Minnesota. There were significantly fewer photo-visitors to Iowa lakes, representing 20 states and no international visitors.

Does photo visitation represent empirical visitation?

Wood et al. (2013) compared empirical visitation to Flickr-photo-estimated visitation from nine datasets representing 836 different natural and cultural attractions worldwide. As expected, photo visitation was an underestimate of total surveyed visitation. However, the relationship between photo visits and surveyed visits was significant and positive (Wood et al. 2013). To evaluate the applicability of the photo-visitation method to lakes, I obtained data from a statewide survey of Iowa lake users conducted by Iowa State University (Evans et al. 2011). Survey information on lake visitation was reported for five years (2002-2005 and 2009) for 86 lakes in Iowa. I calculated average annual trips per lake over the five years of available data and plotted these values against Flickr-photo visitation (Figure 2). I found good agreement between photo visitation and surveyed visitation to Iowa lakes ($R^2 = 0.65$). These results are similar to the regression between surveyed visits to Minnesota State Parks and Flickr-photo-estimated visitation presented in Wood et al. (2013; $R^2 = 0.70$, Figure 2).

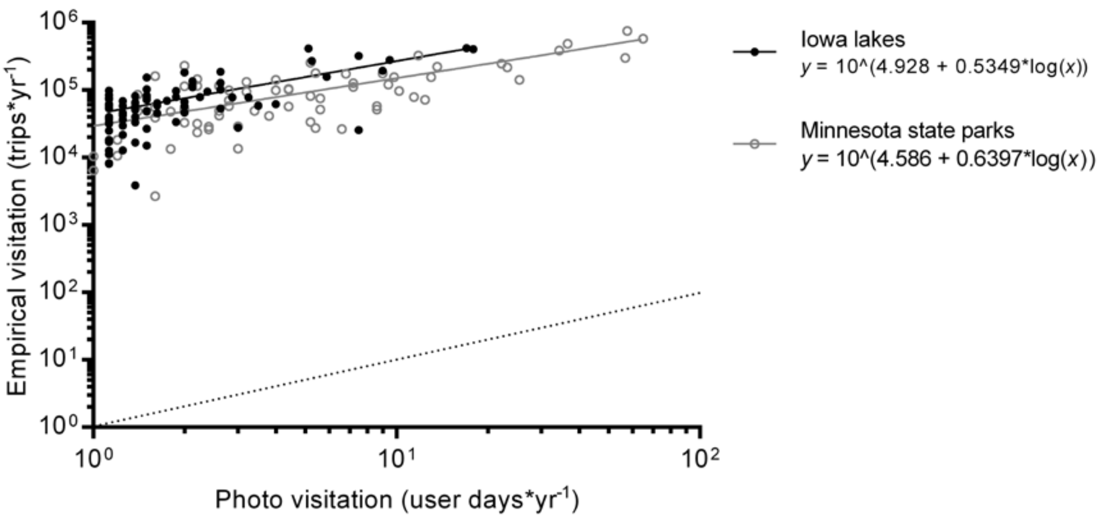


Figure 2: Average photo visitation per year to Iowa lakes and Minnesota state parks compared with empirical visitation from user surveys. Each observation is a lake in Iowa or a state park in Minnesota. Dotted line is a 1:1 relationship between photo visitation and surveyed visitation. Minnesota state park data are adapted from Wood et al. 2013. Trendline equations are non-linear fits of the un-transformed data plotted on log-log axes, where *x* is photo-visitation (user days per year) and *y* is empirical visitation (trips per year). Corresponding R^2 values for each regression are 0.65 (Iowa) and 0.70 (Minnesota).

Lake attributes

To explain variation in photo visitation to lakes I assembled data on a variety of potential explanatory variables including lake water quality, lake depth and size, and near-lake population (Table 1). I also gathered spatial data on the locations of public water access sites, state park and wilderness boundaries, and the presence of aquatic invasive species from the MN Department of Natural Resources (*deli.dnr.state.mn.us/*). Iowa water quality data were provided by Iowa State University as part of the Iowa Lakes Study (*http://www.card.iastate.edu/lakes*, John A. Downing, Iowa State University) and Minnesota water quality data were provided by the Minnesota Pollution Control Agency (MPCA, Steven Heiskary). Spatial data on water access for each lake was joined to the lake polygons in ArcGIS (ESRI ArcMap. 10.2).

Table 1: Lake attributes for Minnesota and Iowa lakes. Iowa lake water quality and clarity data are annual averages from 2005 to 2012 based on three sampling events (early-, mid-, and late-summer). Minnesota clarity data are annual averages from 2005 to 2012 for multiple sampling events per lake per year from May to September.

	Minnesota	**Iowa**
	Mean (Range)	Mean (Range)
Total number of lakes	2103	128
Lake size (acres)	1043 (2 - 302,822)	350 (7 - 5,300)
Lake clarity (m)	2.7 (0.1 - 10.2)	1.1 (0.2 - 5.5)
Lake depth (m)	12.8 (0.3 - 65.5)	6.5 (1.2 - 42.1)
Chlorophyll (ug/L)	19.6 (0.5 - 257.5)	47.9 (2.8 - 187.7)
Total phosphorus (ug/L)	54.3 (1.0 - 492.3)	100.8 (11.7 - 384.8)
Boat launch (1 = yes)	0.57 (0 – 1)	0.27 (0 – 1)
Near-lake population (people)	916,862 (28,456 – 3,460,526)	419,780 (121,512 – 1,088,103)
Average travel time (min)	180 (2 – 853)	163 (21 – 468)
Lake cyanobacteria biomass (mg/L)	No data	138.1 (8.8 – 892.1)
Lake phytoplankton biomass (mg/L)	No data	148.5 (12.6 – 8,987.7)
Lake temperature (C)	No data	24.9 (18.1 – 29.0)
State Park (1 = yes)	0.008 (0 – 1)	No data
Aquatic invasive species (1 = present)	0.3 (0 - 1)	No data

Several lakes were missing water quality data or measurements were only available for a few sampling periods. Water clarity as measured by secchi depth was available for the greatest number of lakes. Long-term average values from 2005 to 2012 were used for most lakes in Iowa and Minnesota. When Minnesota lakes were missing water clarity data from secchi depth measurements, I substituted remotely-sensed water clarity data from the Minnesota Lake Browser (*lakes.gis.umn.edu/*). These lake clarity estimates are based on the relationship between satellite-derived spectral-radiometric responses (color bands) and empirical measurements of lake clarity and are available for the years 2005 and 2008 (Kloiber et al. 2002, Olmanson et al. 2011). The distribution of lake clarity across Iowa and Minnesota is shown in Figure 3. The study region encompasses a wide range of lakes from very clear lakes (greater than 10 meters clarity) to low-clarity lakes (less than 0.5 meter clarity), making it a good study system to evaluate the effects of water quality on lake visitation.

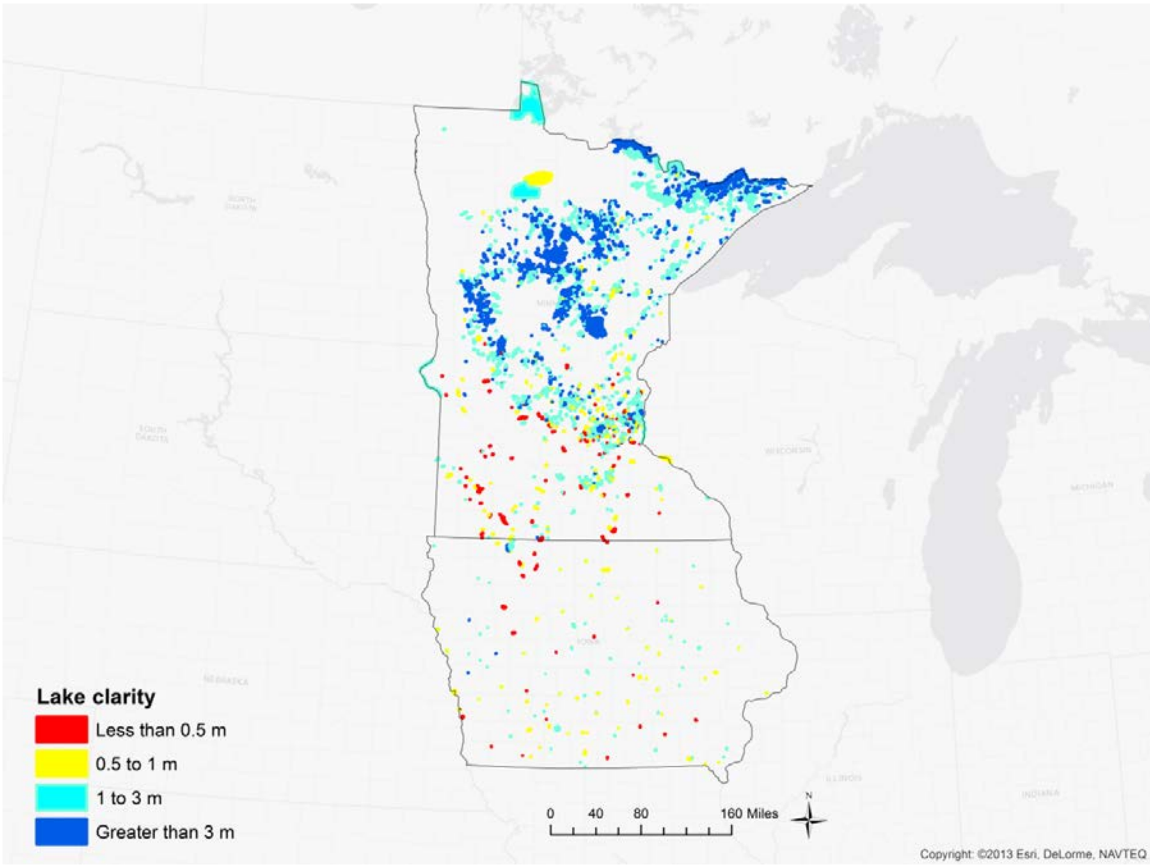


Figure 3: Distribution of lake water clarity in Iowa and Minnesota lakes from 2005 to 2012.

In addition to lake water quality and other lake attributes, I also assigned a population estimate to each lake as an indicator of the number of potential lake visitors living in proximity to each lake. I expected that the number of lake visits would be greater for lakes in densely populated areas than in rural areas. To estimate the population variable for each lake I created a raster layer representing the population density (in people per square mile) from census data for Iowa, Minnesota, neighboring states and Canada. I then created near-lake "visitation-sheds" for each lake representing an 80 km radius (~50 miles) around each lake and summed the number of people living in each lake zone. This distance was selected because it corresponds with the threshold used by the U.S. National Tourism Resources Review Commission to define a tourist (i.e. tourists are individuals traveling greater than 50 miles from their hometown).

Photo-data can also be used to estimate the distance traveled or time spent from a user's stated home location to a lake destination. For the subset of Flickr users that provided information on their locality in their online Flickr profile I mapped each user's hometown to spatial coordinates in a database of populated places (Figure 4). I only considered users with hometowns in nearby Midwestern U.S. states (Minnesota, Michigan, Indiana, Illinois, Iowa, North Dakota, South Dakota, Colorado, Nebraska, Missouri, Kansas, and Wisconsin). Users with reported home localities in other states were assumed to have used air-travel or other modes of transportation to visit Minnesota and Iowa lakes and were excluded from the route analysis.

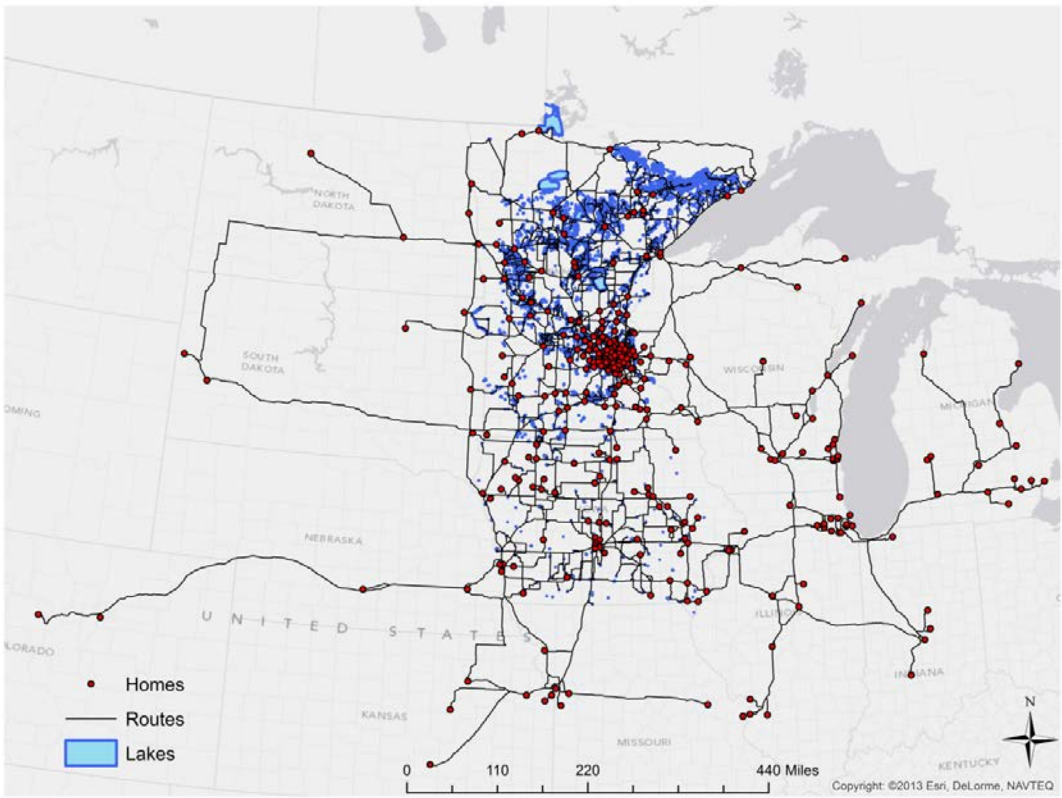


Figure 4: Map of lakes, origins (user hometowns), and routes traveled to visit lakes. Homes and destinations were derived from Flickr photos and routes estimated using ESRI ArcGIS Business Analyst.

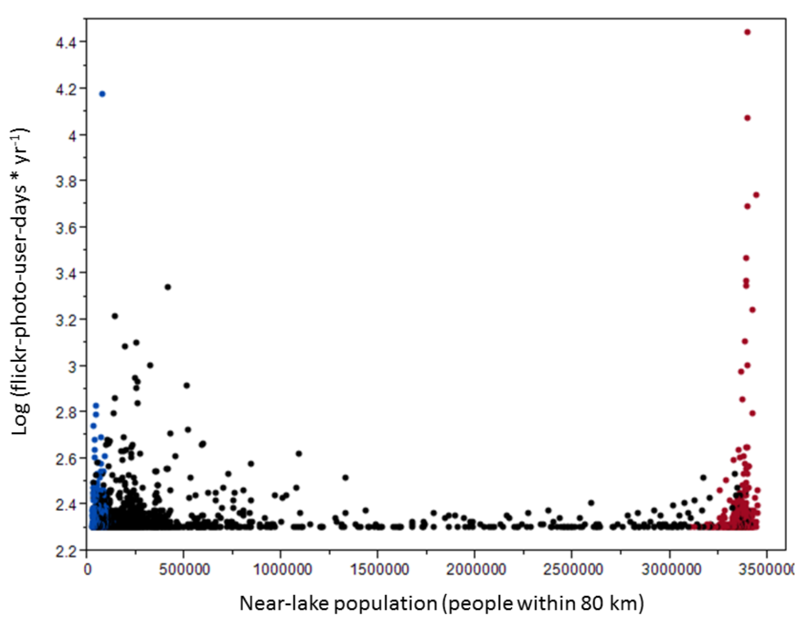
To estimate the distance traveled to visit a lake I used a route analysis in ArcGIS. Each home location and lake destination was assigned an X and a Y coordinate. I used the ESRI ArcGIS Business Analyst Desktop and 2012 NAVTEQ Street Data to estimate the distance traveled and travel time from each home location to visited lake (Figure 4). I eliminated trips where users visited the same lake or nearby lakes on consecutive days. For consecutive-day trips of less than 50 miles (distance from home to lake destination) I assumed users returned home between each lake visit. For trips greater than 50 miles I deleted routes where the same lake or different lakes were visited on consecutive days, assuming that the visitor stayed at or near the lake overnight and did not return home between lake visits. After cleaning consecutive day trips I had a database of 6,438 trips to Minnesota and Iowa lakes from 12 neighboring states (Figure 4). For each lake visited by a Flickr-user with known home location, I estimated the average time and distance traveled to visit that lake. Of the 2,233 lakes in the dataset, 946 were visited by users with home location information and assigned an average travel time value (Table 1).

Results

Does near-lake population affect lake visitation?

As expected, lakes in densely populated areas received the majority of visits (as measured in annual Flickr-photo-user days). However, lakes in sparsely populated areas also received many visits (Figure 5). This relationship was most evident in Minnesota where lakes within the boundaries of the Twin Cities Metropolitan Area were frequently visited, but lakes in very remote and unpopulated parts of the state such as lakes in the Boundary Waters Canoe Area Wilderness were also among the most visited (Figure 5). Due to the bi-modal relationship between lake visitation and near-lake population I centered the population variable in the multiple linear regression model (subtracted mean population from each lake population estimate) and included a squared term for population. There was not a significant relationship between near-lake population and lake visitation for the subset of Iowa lakes.

Figure 5: Relationship between average photo-user-days and population near each lake. Points represent individual lakes. Population surrounding each lake was measured by summing population density within an 80 km radius around each lake. Red points are lakes in the Twin Cities metro area. Blue points are lakes in the Boundary Waters Canoe Area Wilderness.



Which factors predict lake visitation?

If lake visitors value lake water quality, then I would expect more visits to higher quality lakes than to lower quality lakes, accounting for other valued lake attributes. I used multiple linear regression to evaluate the relationship between lake visits and lake-specific explanatory variables (Table 2). I first evaluated state-specific relationships between photo-visitation and explanatory variables (Appendix 3.1). For the final regression models considering both Iowa and Minnesota lakes I excluded variables that were missing from either state (e.g. data on invasive species were not available for Iowa lakes). I also eliminated variables with significant pairwise correlations (see Appendix 3.2). In the combined dataset, lake water clarity was significantly positively correlated with lake depth (deeper lakes tend to be clearer) and negatively correlated with total phosphorus and chlorophyll (Appendix 3.2). Of these variables, lake clarity is the one most likely to be perceived by lake visitors and was available for the greatest number of lake destinations. For these reasons, and because previous work found water clarity was a better proxy for perceived water quality than most other physical water quality attributes (Jeon et al. 2005), I selected clarity as the variable to include (Table 2).

Table 2: Multiple linear regression for lake attributes and photo visitation per lake where the response variable is log(photo-user-days*yr^{-1}). Each observation refers to a lake located in Minnesota or Iowa (n = 2,233 lakes).

	Estimate	SE	Effect test
Intercept	0.097	0.016	<0.0001
Lake size (acres)	5.23E-06	4.40E-07	<0.0001
Lake clarity (m)	0.012	0.003	<0.0001
Centered population	-3.17E-08	1.15E-08	0.0059
Centered population squared	3.92E-14	6.62E-15	<0.0001
Boat launch (1 = yes)	0.038	0.004	<0.0001
Boundary Waters (1 = yes)	0.047	0.008	<0.0001
Iowa or MN (1 = Iowa)	0.060	0.009	<0.0001

I found lake size, lake water clarity, near-lake population, presence of a boat launch, lakes within the Boundary Waters region, and a dummy variable for Iowa or Minnesota to be significant predictors of annual average per-lake visitation (Table 2). The relationship between visitation and lake clarity was positive such that lakes with greater water clarity are associated with increased numbers of visits. As expected, larger lakes also receive more visits than smaller lakes and lakes with a boat launch.

Which factors affect the distance traveled to visit lakes?

In addition to the number of visits to each lake, preference for lake attributes can also be inferred by how far recreationists travel to visit lakes. Individuals have choices in where they spend their recreation time. By using travel time as a proxy for the value individuals place on various lake attributes I can infer how much (in terms of time) users are willing to trade-off to visit lakes of greater water quality accounting for other lake attributes. Again I used multiple linear regression to construct a model of travel time as a function of lake attributes (Table 3).

Table 3: Parameter estimates, standard error (SE) and effect tests for lake attributes used in multiple linear regression model where the response variable is time spent traveling to each lake (one-way). Observations represent all unique combinations of users and lake destinations on non-consecutive days (n = 6438 routes).

	Estimate	SE	Effect test
Intercept	207.50	7.02	<0.0001
Lake size (acres)	0.001	0.00007	<0.0001
Lake clarity (m)	28.07	1.44	<0.0001
Boat launch (1 = yes)	6.51	2.07	0.0017
Boundary waters (1 = yes)	137.83	5.08	<0.0001
Iowa or Minnesota (1 = Iowa)	43.29	3.77	<0.0001

Similar to the analysis of photo user visitation, I found a significant positive relationship between lake water clarity and lake size and travel time, such that longer routes were associated with larger clearer lakes. Longer travel times were also associated with lakes in the Boundary Waters wilderness and lakes with a boat launch. A best fit model estimates that a user is willing to spend an additional 56 minutes in travel time (round-trip) for each additional meter improvement in lake clarity. This translates to approximately $22.26 per trip that a given user is willing to trade-off for improved water quality assuming one-third the average hourly wage rate and a mileage cost of $0.30 per mile (Parsons 2003, Table 4).

Table 4: Estimated average per-lake travel costs associated with increased water clarity. *Median hourly wage estimates from MN and IA are averages for all occupations from the U.S. Bureau of Labor Statistics (2012). Value represents weighted average reflecting the relative proportion of trips to Iowa and Minnesota lakes. The one-third hourly wage adjustment is a commonly-used lower bound estimate used to value time in the recreation literature (Parsons 2003).

Additional travel time per lake due to a 1 m increase in lake clarity (min per round-trip)	Median hourly wage in MN and IA for 2012	One-third of weighted median hourly wage for MN and IA*	Value of wages (wage * travel time)	Value of mileage (0.30 per mile * miles traveled)	Total travel costs
56	$17.74 (MN) and $15.33 (IA)	$5.85	$5.46	$16.80	$22.26

Would improvements to lake water quality increase the number of visits to lakes?

From my analysis, there is evidence to suggest that lake recreationists visit clear lakes more often than less-clear lakes and travel greater distances to visit lakes of higher quality. To estimate how a change in water quality would affect the number of visits to lakes, I use the estimated relationship from the regression equation specified in Table 2. I estimate the change in photo-visitation between a scenario of baseline water clarity and for a scenario where the water clarity of all lakes is increased by one-meter. If I assume that the relationship between photo-visitation and surveyed visitation to Iowa lakes holds for all lakes in the sample region, I can convert the model estimates of the change in photo-visitation into an estimate of annual trips per lake (based on data presented in Figure 2). Using this approach I calculate an average increase of 1,136 annual trips per lake (1,094 to 1,183 lower and upper 95% mean confidence limits) as a result of a one meter increase in lake water clarity (estimated from the regression equation specified in Table 2).

I estimate the value associated with increased trips using data on average daily trip expenditures from the U.S. Fish and Wildlife Survey of Fishing, Hunting, and Wildlife-Associated Recreation (US FWS 2011). I multiplied the estimated increase in recreational trips due to improved water clarity by values of trip-related expenditures for Iowa and Minnesota residents from the US FWS survey. Assuming a weighted average per trip expenditure of $40.69 ($17 per trip for activities in Iowa and $43 per trip for activities in Minnesota) I estimate a per lake increase in value of $44,519 to $48,141 per year due to improved water quality (based on lower and upper confidence limits for mean increases in trips per lake from Table 2). These per-trip expenditures reflect the costs of food, lodging, and transportation associated with an average visit and are not equivalent to consumer surplus, or the additional welfare generated by a change in water clarity. Multiplying the trip expenditures by the estimated increased visits for the total number of lakes in the region would yield a large value. However, this would also assume that as lake water quality improves it generates additional visits to each lake, instead of shifting allocation of visits from some lakes to others. In reality, recreationists have a finite number of trips they can spend in a given time period and improved water quality may increase the total number of visits slightly, but will more likely shift visits from other recreational activities or away from lower-quality sites.

Discussion and Conclusions

I used photo visitation data to understand the role of lake water quality in the behavior of lake recreationists and the value lake users place on water quality. I found that lake users visit clear lakes more often than less-clear lakes and they are willing to trade-off more of their time and travel expenses to visit higher quality lakes. Other studies investigating the value of lake water quality have found similar evidence for the role of water clarity in lake visitation (Feather et al. 1995, Phaneuf et al. 2002, Egan et al. 2009, Ge et al. 2013). Unlike these studies, my approach is easily replicable to any decision context at low cost without relying on survey data.

I estimate a per trip willingness-to-pay of $22 and increased visits representing trip-related expenditures of $44,519 to 48,141 annually per lake due to a one meter change in lake clarity. Ge et al (2013) used a meta-analysis of contingent valuation and travel cost studies to assess the economic value of a similar water quality change and found an annual per household willingness to pay of $45 for a one meter improvement in lake clarity. They also found that people are willing to pay more to avoid degradation than to invest in improvements in degraded water quality (Ge et al. 2013). Krysel et al. (2003) also considered the value of a one meter increase in lake clarity through assessment of changes to lakeshore property values in the Mississippi Headwaters region of Minnesota. They found increased water clarity resulted in an average property value increase of $5.8 million per lake.

While these estimates are illustrative of the value placed on lakes, the most policy-relevant value information describes how a given change in quality at an individual lake may affect site-specific demand for recreation. More complex random utility models offer the ability to estimate welfare associated with specific water quality improvements (Bockstael et al. 1987, Hicks and Strand 2000, Phaneuf 2002). A random utility model estimates the probability that an individual user will visit a given lake on a particular choice occasion as a function of lake attributes and other variables. The random utility model assumes that a user will chose to maximize their utility by selecting the lake that represents the most enjoyment at the lowest travel cost. These models require researchers to specify the choice set from which individuals chose a recreation destination. Because the choice set of potential sites in my study is large (over 2,000 lakes) and I have limited information on the choices made by individual users, it is difficult to apply a random utility model. In the future, I plan to use geo-spatial clustering techniques (see Popescu and Grefenstette 2010, Jahanbakhsh et al. 2012) to identify hometown information for all lake users taking photos (not just those providing this information in their user profile) which would greatly increase the sample size of user-lake combinations with route information.

It is important to note that the value estimates associated with changes in lake recreation are not representative of the full value of a given change in water quality. Water quality changes affect multiple water-related ecosystem services which are additive to changes in recreational value (Keeler et al. 2012). These include health effects associated with drinking or contact with contaminated water and non-use values, both of which can make up significant percentage of the total value associated with a given change in water quality (Bockstael et al. 1989, Johnston et al. 2003, Townsend et al. 2003).

There are several advantages of my approach over survey methods or site counts. Photo-visitation data are considerably less expensive and time consuming to collect. Large sets of lakes or other attractions can be evaluated quickly, making it easy to scale analyses. My method also allows researchers to capture information on all visits, not just those originating from in-state users. I found almost 40% of lake visits originated from out of state, information that would not have been captured on survey instruments targeting in-state residents.

There are also disadvantages to the photo-visitation methodology. I know that Flickr-users are not necessarily representative of all recreationists (Li et al. 2013). Their behavior and preferences may differ from those of the true set of lake users. At present, I know very little about why Flickr-users take photos, what activities they were engaging in while at the lake, and how those activities differ from other lake users. Many lakes received less than one photo per year on average resulting in small sample sizes for many lake observations. As the usage of photo-sharing websites and other geo-tagged social media increases, it will increase the robustness of photo-visitation estimates. Despite these limitations, my validation comparison using Iowa lake data and previous work across multiple sites (Wood et al. 2013) suggests that photo-visitation is a reliable proxy for empirical visitation.

Evidence that people prefer to recreate in higher quality lakes may not seem surprising. However, there are many factors that may explain patterns of lake visitation and it is notable that water quality still emerges as an important predictor even when accounting for other variables. This paper contributes information on how recreational value changes with changes in water quality, research that is needed to inform regulatory cost-benefit assessments (Griffiths et al. 2012). Next steps for adapting this approach include scaling up to link photo-visitation estimates to regional and national databases on lake water quality. These data can be overlain with data on known impairments to evaluate the return on investments to improve surface water quality from a single lake up to state or regional-scales. In the future, I expect geo-tagged data on recreational demand to advance spatial planning, inform resource investments, and improve our understanding of the behavior and preferences of surface-water users.

Bibliography

Alexander Jr, E., R. Lively. 1995. Karst–aquifers, caves, and sinkholes. Geologic Atlas of Fillmore County, Minnesota:10-18.

Anderson, D. M., P. M. Glibert, and J. A. M. Burkholder. 2002. Harmful algal blooms and eutrophication: nutrient sources, composition, and consequences. Estuaries and Coasts 25:704-726.

Arnold, J., N. Fohrer, and A. USDA. 2005. SWAT2000: current capabilities and research opportunities in applied watershed modelling. Hydrological Processes 19:563-572.

Bateman IJ, Mace GM, Fezzi C, Atkinson G & Turner K. 2011. Economic analysis for ecosystem service assessments. Environmental and Resource Economics 48:177-218.

Beman, J. M., K. R. Arrigo, and P. A. Matson. 2005. Agricultural runoff fuels large phytoplankton blooms in vulnerable areas of the ocean. Nature 434:211-214.

Bockstael, N. E., K. E. McConnell, and I. Strand. 1989. Measuring the benefits of improvements in water quality: The Chesapeake Bay. Marine Resource Economics 6:1-18.

Bockstael, N. E., W. M. Hanemann, and C. L. Kling. 1987. Estimating the value of water quality improvements in a recreational demand framework. Water Resources Research 23:951-960.

Bockstael, N.E., R. Costanza, I. Strand, W. Boynton, K. Bell, and L. Wainger. 1995. Ecological and economic modeling and valuation of ecosystems. Ecological Economics 14:143-159.

Bockstael, N., A. Freeman, R. Kopp, P. Portney, and V. Smith. 2000. On measuring economic values for nature. Environmental Science & Technology 34:1384-1389.

Boyle, K.J., and R. Brouchard. 2003. Water quality effects on property prices in northern New England. Lake Line 23:2427.

Brauman, K. A., G. C. Daily, T. K. Duarte, and H. A. Mooney. 2007. The nature and value of ecosystem services: An overview highlighting hydrologic services. Annu.Rev.Environ.Resour. 32:67-98.

Breitburg, D., J. Craig, R. Fulford, K. Rose, W. Boynton, D. Brady, B. Ciotti, R. Diaz, K. Friedland, and J. Hagy. 2009. Nutrient enrichment and fisheries exploitation: Interactive effects on estuarine living resources and their management. Hydrobiologia 629:31-47.

Brender, J. D., P. J. Weyer, P. A. Romitti, B. P. Mohanty, M. U. Shinde, A. M. Vuong, J. R. Sharkey, D. Dwivedi, S. A. Horel, and J. Kantamneni. 2013. Prenatal Nitrate Intake from Drinking Water and Selected Birth Defects in Offspring of Participants in the National Birth Defects Prevention Study. Environmental Health Perspectives. http://dx.doi.org/10.1289/ehp.1206249

Burow, K. R., B. T. Nolan, M. G. Rupert, and N. M. Dubrovsky. 2010. Nitrate in groundwater of the United States, 1991− 2003. Environmental Science & Technology 44:4988-4997.

Carbó, L., M. Flores, and M. Herrero. 2009. Well site conditions associated with nitrate contamination in a multilayer semiconfined aquifer of Buenos Aires, Argentina. Environmental Geology 57:1489-1500.

Carpenter S. R., H. A. Mooney, J. Agard, D. Capistrano, R. S. DeFries, S. Diaz, T. Dietz, A. K. Duraiappah, A. Oteng-Yeboah, H. M. Pereira, C. Perrings, W. V. Reid, J. Sarukhan, R. J. Scholes, and A. Whyte. 2009. Science for managing ecosystem services: Beyond the Millennium Ecosystem Assessment. Proceedings of the National Academy of Sciences of the United States of America 106:1305-1312.

Carson, R. T., R. C. Mitchell. 1993. The value of clean water: The public's willingness to pay for boatable, fishable, and swimmable quality water. Water Resources Research 29:2445-2454.

Champ, P.A., K.J. Boyle, T.C. Brown. (eds.) 2003. A primer on nonmarket valuation. KluIr Academic Publishers. Netherlands.

Comly, H. H. 1945. Cyanosis in infants caused by nitrates in well water. Journal of the American Medical Association 257:2788-2792..

Compton, J. E., J. A. Harrison, R. L. Dennis, T. L. Greaver, B. H. Hill, S. J. Jordan, H. Walker, and H. V. Campbell. 2011. Ecosystem services altered by human changes in the nitrogen cycle: A new perspective for US decision making. Ecology Letters 14:804-815.

Corrigan, J. R., K. J. Egan, and J. A. Downing. 2007. Aesthetic Values of Lakes and Rivers. Working Papers. Kenyon College, Department of Economics. Available: *http://economics.kenyon.edu/corrigan/publications/Aesthetic%20Values%20of%20Lakes%20and%20Rivers.pdf.* Accessed: 11/25/13.

Costanza, R., R. dArge, R. deGroot, S. Farber, M. Grasso, B. Hannon, K. Limburg, S. Naeem, R. ONeill, J. Paruelo, R. Raskin, P. Sutton, and M. vandenBelt. 1997. The value of the world's ecosystem services and natural capital. Nature 387:253-260.

Costello, C., W. M. Griffin, A. E. Landis, and H. S. Matthews. 2009. Impact of biofuel crop production on the formation of hypoxia in the Gulf of Mexico. Environmental Science & Technology 43:7985-7991.

Culman, S. W., A. Young-Mathews, A. D. Hollander, H. Ferris, S. Sánchez-Moreno, A. T. O'Geen, and L. E. Jackson. 2010. Biodiversity is associated with indicators of soil ecosystem functions over a landscape gradient of agricultural intensification. Landscape Ecology 25:1333-1348.

Cropper, M. L., W. Isaac. 2011. The Benefits of Achieving the Chesapeake Bay TMDLs (Total Maximum Daily Loads): A Scoping Study. Discussion Papers. Resources for the Future. RFF DP 11-31.

Daily, G. C. 1997. Nature's services: Societal dependence on natural ecosystems. Island Press, Washington, D.C.

Daily, G. C., S. Polasky, J. Goldstein, P. M. Kareiva, H. A. Mooney, L. Pejchar, T. H. Ricketts, J. Salzman, and R. Shallenberger. 2009. Ecosystem services in decision making: Time to deliver. Frontiers in Ecology and the Environment 7:21-28.

Davenport, T. E., S. A. Dressing, and D. W. Meals. 2010. Lag time in water quality response to best management practices: A review. Journal of Environmental Quality 39:85-96.

De Roos, A., M. Ward, C. Lynch, and K. Cantor. 2003. Nitrate in public water supplies and the risk of colon and rectum cancers. Epidemiology 14:640-649.

Diaz, R. J., R. Rosenberg. 2011. Introduction to Environmental and Economic Consequences of Hypoxia. International Journal of Water Resources Development 27:71-82.

Dodds, W. K., W. W. Bouska, J. L. Eitzmann, T. J. Pilger, K. L. Pitts, A. J. Riley, J. T. Schloesser, and D. J. Thornbrugh. 2009. Eutrophication of US Freshwaters: Analysis of Potential Economic Damages. Environmental Science & Technology 43:12-19.

Doi, H., I. Katano, J.N. Negishi, S. Sanada, and Y. Kayaba. 2013. Effects of biodiversity, habitat structure, and water quality on recreational use of rivers. Ecosphere 4: http://dx.doi.org/10.1890/ES12-00305.1.

Donner, S.D., C.J. Kucharik. 2008. Corn-based ethanol production compromises goal of reducing nitrogen export by the Mississippi River. Proceedings of the National Academy of Sciences 105:4513-4518.

Dumas, C.F., P.W. Schuhmann, J.C. Whitehead. 2005. Measuring the economic benefits of water quality improvement with benefit transfer: An introduction for noneconomists. American Fisheries Society Symposium. American Fisheries Society; 53 p.

Eaton J.G. and R. M. Scheller. 1996. Effects of climate warming on fish thermal habitat in streams of the United States. Journal of Limnology and Oceanography. 41:1109-1115.

Egan, K. J., J. A. Herriges, C. L. Kling, and J. A. Downing. 2009. Valuing water quality as a function of water quality measures. American Journal of Agricultural Economics 91:106-123.

Euliss Jr, N. H., L. M. Smith, S. Liu, M. Feng, D. M. Mushet, R. F. Auch, and T. R. Loveland. 2010. The need for simultaneous evaluation of ecosystem services and land use change. Environmental Science & Technology 44:7761-7763.

Euliss Jr N. H., L. M. Smith, S. Liu, W. G. Duffy, S. P. Faulkner, R. A. Gleason, and S. D. Eckles. 2011. Integrating estimates of ecosystem services from conservation programs and practices into models for decision makers. Ecological Applications 21:128-134.

Evans, K.S., J.A. Herriges, C.L. Kling. 2011. Iowa Lakes Survey 2009. A Report to the Iowa Department of Natural Resources on The Iowa Lakes Valuation Project 2009: Summary and Findings. Available at: *http://www.card.iastate.edu/lakes/iowa-lakes-report-2009.pdf*. Accessed: 11/25/13.

Faber, S., S. Rundquist, and T. Male. 2012. Plowed under: How crop subsidies contribute to massive habitat losses. Environmental Working Group, Washington, D.C.

Fan, A., C. Willhite, and S. Book. 1987. Evaluation of the Nitrate Drinking-Water Standard with Reference to Infant Methemoglobinemia and Potential Reproductive Toxicity. Regulatory Toxicology and Pharmacology 7:135-148.

Feather, P., D. Hellerstein, and T. Tomasi. 1995. A discrete-count model of recreational demand. Journal of Environmental Economics and Management 29:214-227.

Fisher, B., K. Turner, M. Zylstra, R. Brouwer, R. Groot, S. Farber, P. Ferraro, R. Green, D. Hadley, and J. Harlow. 2008. Ecosystem services and economic theory: Integration for policy-relevant research. Ecological Applications 18:2050-2067.

Freeman, A.M. III. 2003. The measurement of environmental and resource values: Theory and methods. Washington, D.C.: Resources for the Future.

Funtowicz S. O., J. R. Ravetz. 1993. Science for the post-normal age. Futures 25:739-755.

Gardner, K. K., R. M. Vogel. 2005. Predicting ground water nitrate concentration from land use. Ground Water 43:343-352.

Ge, J., C. Kling, J. Herriges. 2013. How much is clean water worth? Valuing water quality improvement using a meta-analysis. Available at: *http://www.card.iastate.edu/environment/items/valuing-water-quality.pdf*. Accessed: 11/25/13.

Gilliom, R. J. 2007. Pesticides in US streams and groundwater. Environmental Science & Technology 41:3408-3414.

Griffiths, C., H. Klemick, M. Massey, C. Moore, S. Newbold, D. Simpson, P. Walsh, and W. Wheeler. 2012. US Environmental Protection Agency valuation of surface water quality improvements. Review of Environmental Economics and Policy 6:130-146.

Gurdak, J. J., S. L. Qi. 2012. Vulnerability of recently recharged groundwater in principle aquifers of the United States to nitrate contamination. Environmental Science & Technology 46:6004-6012.

Haab, T. C., R. L. Hicks. 1997. Accounting for choice set endogeneity in random utility models of recreation demand. Journal of Environmental Economics and Management 34:127-147.

Harkanpar, K. 2008. Nitrate pollution externality associated with increased corn demand for ethanol: A case study of Olmsted County in Minnesota. The 82nd Annual Conference of the Agricultural Economics Society, Royal Agricultural College.

Heiskary, S. A., W. W. Walker Jr. 1988. Developing phosphorus criteria for Minnesota lakes. Lake and Reservoir Management 4:1-9.

Heisler, J., P. Glibert, J. Burkholder, D. Anderson, W. Cochlan, W. Dennison, Q. Dortch, C. Gobler, C. Heil, and E. Humphries. 2008. Eutrophication and harmful algal blooms: A scientific consensus. Harmful Algae 8:3-13.

Hicks, R., I. Strand. 2000. The extent of information: Its relevance for random utility models. Land Economics 76:374-385.

Huang, L., M. D. Smith. 2011. Management of an annual fishery in the presence of ecological stress: The case of shrimp and hypoxia. Ecological Economics 70:688-697.

Hulse D., R. Ribe. 2000. Land conversion and the production of wealth. Ecological Applications 10:679-682.

Iovanna, R., C. Griffiths. 2006. Clean water, ecological benefits, and benefits transfer: A work in progress at the US EPA. Ecological Economics 60:473-482.

Isaak, D. J., W. A. Hubert. 2004. Nonlinear response of trout abundance to summer stream temperatures across a thermally diverse montane landscape. Transactions of the American Fisheries Society 133:1254-1259.

Jahanbakhsh, K., V. King, and G. C. Shoja. 2012. They Know Where You Live! Working Paper, University of Victoria, Computer Science Department, British Columbia.

Jeon, Y., J. A. Herriges, C. L. Kling, and J. Downing. 2005. The role of water quality perceptions in modeling lake recreation demand. Working Paper no. 05032. Iowa State University. Available at: *http://www.econ.iastate.edu/research/working-papers/p3840*. Accessed: 11/25/13.

Johnston, R., E. Besedin, and R. Wardell. 2003. Modeling relationships between use and nonuse values for surface water quality: A meta-analysis. Water Resources Research 39: DOI: 10.1029/2003WR002649

Johnston, R., E. Besedin, R. Iovanna, C. Miller, R. Wardwell, and M. Ranson. 2005. Systematic variation in willingness to pay for aquatic resource improvements and implications for benefit transfer: a meta-analysis. Canadian Journal of Agricultural Economics-Revue Canadienne D Agroeconomie 53:221-248.

Johnston, C. A. 2013. Agricultural expansion: land use shell game in the US Northern Plains. Landscape Ecology DOI 10.1007/s10980-013-9947-0.

Keeler, B., S. Polasky, K. Brauman, K. Johnson, J. Finlay, A. O'Neill, K. Kovacs, B. Dalzell. 2013. Linking water quality and well-being for improved assessment and valuation of ecosystem services. Proceedings of the National Academy of Sciences 109:18619-18624.

Kellogg, D., A. J. Gold, S. Cox, K. Addy, and P. V. August. 2010. A geospatial approach for assessing denitrification sinks within lower-order catchments. Ecological Engineering 36:1596-1606.

Kinzig, A., C. Perrings, F. Chapin III, S. Polasky, V. Smith, D. Tilman, and B. Turner II. 2011. Paying for Ecosystem Services—Promise and Peril. Science 334:603-604.

Kloiber, S. M., P. L. Brezonik, and M. E. Bauer. 2002. Application of Landsat imagery to regional-scale assessments of lake clarity. Water Research 36:4330-4340.

Krysel, C., E.M. Boyer, C. Parson, P. Welle. 2003. Lakeshore property values and water quality: Evidence from property sales in the Mississippi Headwaters Region. Submitted to the Legislative Commission on Minnesota Resources, by Mississippi Headwaters Board and Bemidji State University.

Kuhn T. S. 1962. The Structure of Scientific Revolutions. The University of Chicago Press, Chicago, IL.

Lewandowski, A. M. 2008. Costs of groundwater nitrate contamination. Journal of Soil and Water Conservation 63:92A-92A.

Li, L., M. F. Goodchild, and B. Xu. 2013. Spatial, temporal, and socioeconomic patterns in the use of Twitter and Flickr. Cartography and Geographic Information Science 40:61-77.

Lichtenberg, E., L. K. Shapiro. 1997. Agriculture and nitrate concentrations in Maryland community water system wells. Journal of Environmental Quality 26:145-153.

Lipton D. 2004. The value of improved water quality to Chesapeake Bay boaters. Marine Resource Economics 19:265-270.

Liu, A., J. Ming, and R. O. Ankumah. 2005. Nitrate contamination in private wells in rural Alabama, United States. Science of the Total Environment 346:112-120.

Liu S., R. Costanza, A. Troy, J. D'Aagostino, and W. Mates. 2010. Valuing New Jersey's ecosystem services and natural capital: A spatially explicit benefit transfer approach. Environmental management 45:1271-1285.

MA [Millennium Ecosystem Assessment]. 2005. Millennium ecosystem assessment. Ecosystems and Human Well-Being: Synthesis Washington DC: Island Press.

Mair, A., A. I. El-Kadi. 2013. Logistic regression modeling to assess groundwater vulnerability to contamination in Hawaii, USA. Journal of Contaminant Hydrology 153:1-23.

Mathews, L. G., F. R. Homans, and K. W. Easter. 2002. Estimating the benefits of phosphorus pollution reductions: An application in the Minnesota River. Journal of the American Water Resources Association 38:1217-1223.

McCauley D. J. 2006. Selling out on nature. Nature 443:27-28.

Michael, H.J., K.J. Boyle, R. Bouchard. 1996. Water quality affects property prices: A case study of selected Maine lakes. University of Maine. Miscellaneous Report, no. 398. Available: *http://www.umaine.edu/mafes/elec_pubs/miscrepts/mr398.pdf*. Accessed: 11/25/13.

MPCA, Minnesota Pollution Control Agency. 2013. The condition of Minnesota's groundwater, 2007 - 2011. August, 2013.

Moore, E., E. Matalon, C. Balazs, J. Clary, L. Firestone, S. De Anda, M. Guzman, N. Ross, and P. Luu. 2011. The Human Costs of Nitrate-contaminated Drinking Water in the San Joaquin Valley, The Pacific Institute.

Mossler, J.H. 2008. Paleozoic stratigraphic nomenclature for Minnesota: Minnesota Geological Survey Report of Investigations 65, 76 p., 1 pl.

Mubarak K. 2003. Utilizing GIS to Estimate The Quantity and Distribution of Nitrate-Nitrogen And Chloride in Olmsted County Groundwater. St. Mary's University of Minnesota, Winona, MN.

Nelson E., S. Polasky, D. J. Lewis, A. J. Plantingall, E. Lonsdorf, D. White, D. Bael, and J. J. Lawler. 2008. Efficiency of incentives to jointly increase carbon sequestration and species conservation on a landscape. Proceedings of the National Academy of Sciences of the United States of America 105:9471-9476.

Nelson E., G. Mendoza, J. Regetz, S. Polasky, H. Tallis, D. R. Cameron, K. M. A. Chan, G. C. Daily, J. Goldstein, and P. M. Kareiva. 2009. Modeling multiple ecosystem services, biodiversity conservation, commodity production, and tradeoffs at landscape scales. Frontiers in Ecology and the Environment 7:4-11.

Nelson E. J., G. C. Daily. 2010. Modeling ecosystem services in terrestrial systems. F1000 Biology Reports.

Noe, R, H. Heavenrich, L. Nachman, B. Keeler, D. Hernandez, and J. Hill. Valuing the ecosystem services of diverse prairie as a biofuel feedstock in southern Minnesota. *In prep* for Environmental Science & Technology.

Nolan, B. T., K. J. Hitt. 2006. Vulnerability of shallow groundwater and drinking-water wells to nitrate in the United States. Environmental Science & Technology 40:7834-7840.

Nolan, B. T., K. J. Hitt, and B. C. Ruddy. 2002. Probability of nitrate contamination of recently recharged groundwaters in the conterminous United States. Environmental Science & Technology 36:2138-2145.

Norton B. G. 1998. Improving ecological communication: The role of ecologists in environmental policy formation. Ecological Applications 8:350-364.

O'Connor, T., D. Whitall. 2007. Linking hypoxia to shrimp catch in the northern Gulf of Mexico. Marine Pollution Bulletin 54:460-463.

Olmstead S. M. 2010. The Economics of Water Quality. Review of Environmental Economics and Policy 4:44-62.

Olmanson, L. G., P. L. Brezonik, and M. E. Bauer. 2011. Evaluation of medium to low resolution satellite imagery for regional lake water quality assessments. Water Resources Research 47: doi :10.1029/2011WR011005.

Parsons, G. R., M. J. Kealy. 1992. Randomly drawn opportunity sets in a random utility model of lake recreation. Land Economics 68:93-106.

Parsons, G.R., 2003. The travel cost model. In: A primer on nonmarket valuation. Eds. P.A. Champ, K.J. Boyle, T.C. Brown. KluIr Academic Publishers. Netherlands. p. 269-330.

Perrings C., S. Naeem, F. S. Ahrestani, D. E. Bunker, P. Burkill, G. Canziani, T. Elmqvist, J. A. Fuhrman, F. M. Jaksic, and Z. Kawabata. 2011. Ecosystem services, targets, and indicators for the conservation and sustainable use of biodiversity. Frontiers in Ecology and the Environment 9:512-520.

Phaneuf, D. J. 2002. A random utility model for total maximum daily loads: Estimating the benefits of watershed-based ambient water quality improvements. Water Resources Research 38:1-11.

Phaneuf, D. J., V. K. Smith. 2005. Recreation demand models. Handbook of Environmental Economics 2:671-761.

Polasky S., S. R. Carpenter, C. Folke, and B. Keeler. 2011a. Decision-making under great uncertainty: environmental management in an era of global change. Trends in Ecology & Evolution 26:398-404.

Polasky S., E. Nelson, D. Pennington, and K. A. Johnson. 2011b. The Impact of Land-Use Change on Ecosystem Services, Biodiversity and Returns to Landowners: A Case Study in the State of Minnesota. Environmental & Resource Economics 48:219-242.

Popescu, A., and G. Grefenstette. 2010. Mining user home location and gender from Flickr tags. Proceedings of the Fourth International AAAI Conference on weblogs and Social Media. p.307-310.

Porcher, E. 1989. Groundwater contamination susceptibility in Minnesota. Minnesota Pollution Control Agency.

Powlson, D. S., T. M. Addiscott, N. Benjamin, K. G. Cassman, T. M. de Kok, H. van Grinsven, J. L'hirondel, A. A. Avery, and C. Van Kessel. 2008. When does nitrate become a risk for humans? Journal of Environmental Quality 37:291-295.

Preis, T., H. S. Moat, S. R. Bishop, P. Treleaven, and H. E. Stanley. 2013. Quantifying the digital traces of Hurricane Sandy on Flickr. Scientific Reports 3:3141.

Railsback, S., K. Rose. 1999. Bioenergetics modeling of stream trout growth: Temperature and food consumption effects. Transactions of the American Fisheries Society 128:241-256.

Reckhow, K., J. Simpson. 1980. A procedure using modeling and error analysis for the prediction of lake phosphorus concentration from land use information. Canadian Journal of Fisheries and Aquatic Sciences 37:1439-1448.

Runkel, A.C., R.G. Tipping, E.C. Alexander, Jr., J.A. Green, J.H. Mossler, and S.C. Alexander. 2003. Hydrogeology of the Paleozoic bedrock in southeastern Minnesota. Minnesota Geologic Survey Report of Investigations 61, 105.

Runkel, A.C., J.R. Steenberg, R.G. Tipping, A.J. Retzler. 2013. Geologic controls on groundwater and surface water flow in southeastern Minnesota and its impact on nitrate concentrations in streams. Minnesota Geologic Survey.

Scheffer, M., S. Hosper, M. Meijer, B. Moss, and E. Jeppesen. 1993. Alternative equilibria in shallow lakes. Trends in Ecology & Evolution 8:275-279.

Scheffer, M., S. Carpenter, J. A. Foley, C. Folke, and B. Walker. 2001. Catastrophic shifts in ecosystems. Nature 413:591-596.

Schilling, K. E., J. Spooner. 2006. Effects of watershed-scale land use change on stream nitrate concentrations. Journal of Environmental Quality 35:2132-2145.

Sebilo, M., B. Mayer, B. Nicolardot, G. Pinay, and A. Mariotti. 2013. Long-term fate of nitrate fertilizer in agricultural soils. Proceedings of the National Academy of Sciences 110:18185-18189.

Secchi, S., P. W. Gassman, M. Jha, L. Kurkalova, and C. L. Kling. 2011. Potential water quality changes due to corn expansion in the Upper Mississippi River Basin. Ecological Applications 21:1068-1084.

Smith, V. K., W. H. Desvousges, and A. Fisher. 1986. A comparison of direct and indirect methods for estimating environmental benefits. American Journal of Agricultural Economics 68:280-290.

Smith, K. A., T. D. Searchinger. 2012. Crop-based biofuels and associated environmental concerns. Global Change Biology Bioenergy 4:479-484.

Spalding, R. F., M. E. Exner. 1993. Occurrence of nitrate in groundwater—A review. Journal of Environmental Quality 22:392-402.

Steinnes, D. 1992. Measuring the economic value of water quality: The case of lakeshore land. Annals of Regional Science 26:171-176.

Stephens, S. E., J. A. Walker, D. R. Blunck, A. Jayaraman, D. E. Naugle, J. K. Ringelman, and A. J. Smith. 2008. Predicting risk of habitat conversion in native temperate grasslands. Conservation Biology 22:1320-1330.

Sun, Y., H. Fan, M. Helbich, and A. Zipf. 2013. Analyzing human activities through volunteered geographic information: Using Flickr to analyze spatial and temporal pattern of tourist accommodation. Progress in Location-Based Services 57-69.

Sutton, M. A., C. M. Howard, and J. W. Erisman. 2011. The European nitrogen assessment: Sources, effects and policy perspectives. Cambridge University Press.

Tallis H., S. Polasky. 2009. Mapping and Valuing Ecosystem Services as an Approach for Conservation and Natural-Resource Management. Annals of the New York Academy of Sciences 1162:265-283.

Tallis, H., T. Ricketts, E. Nelson, D. Ennaanay, S. Wolny, N. Olwero, K. Vigerstol, D. Pennington, G. Mendoza, J. Aukema, J. Foster, J. Forrest, E. Lonsdorf, and C. Kennedy. 2011. InVEST 2.0 beta User's Guide. Integrated Valuation of Ecosystem Services and Tradeoffs. The Natural Capital Project, Stanford, CA.

Tesoriero, A. J., F. D. Voss. 1997. Predicting the probability of elevated nitrate concentrations in the Puget Sound Basin: Implications for aquifer susceptibility and vulnerability. Ground Water 35:1029-1039.

Tesoriero, A. J., T. B. Spruill, and J. L. Eimers. 2004. Geochemistry of shallow ground water in coastal plain environments in the southeastern United States: Implications for aquifer susceptibility. Applied Geochemistry 19:1471-1482.

Thompson, B. H., K. Segerson. 2009. Valuing the Protection of Ecological Systems and Services Report. 1-138p.

Tipping, R., J. Green, and E. Alexander Jr. 2001. Karst features, pl. 5 of Runkel, AC, project manager, Geologic atlas of Wabasha County, Minnesota: Minnesota Geological Survey County Atlas C-14, pt.

Tomer, M., M. Burkart. 2003. Long-term effects of nitrogen fertilizer use on ground water nitrate in two small watersheds. Journal of Environmental Quality 32:2158-2171.

Tomer, M., K. Schilling, C. Cambardella, P. Jacobson, and P. Drobney. 2010. Groundwater nutrient concentrations during prairie reconstruction on an Iowa landscape. Agriculture, Ecosystems & Environment 139:206-213.

Townsend, A. R., R. W. Howarth, F. A. Bazzaz, M. S. Booth, C. C. Cleveland, S. K. Collinge, A. P. Dobson, P. R. Epstein, E. A. Holland, and D. R. Keeney. 2003. Human health effects of a changing global nitrogen cycle. Frontiers in Ecology and the Environment 1:240-246.

[US EPA] U.S. Environmental Protection Agency. 2011. Drinking water contaminants: National primary drinking water regulations.

[US FWS] U.S. Fish and Wildlife Service. 2011. National survey of hunting, fishing, and wildlife-associated recreation. Available at: *wsfrprograms.fws.gov*/. Accessed 11/25/13.

[US BLS] U.S. Bureau of Labor Statistics. 2012. May 2012 National Occupational Employment and Wage Estimates. Available at: *http://www.bls.gov/oes/current/oes_nat.htm*. Accessed 11/25/13.

Van Houtven, G., J. Powers, and S. K. Pattanayak. 2007. Valuing water quality improvements in the United States using meta-analysis: Is the glass half-full or half-empty for national policy analysis? Resource and Energy Economics 29:206-228.

van Grinsven, H. J. M., A. Rabl, and T. M. de Kok. 2010. Estimation of incidence and social cost of colon cancer due to nitrate in drinking water in the EU: A tentative cost-benefit assessment. Environmental Health 9:58-69.

Villa F., M. Ceroni, K. Bagstad, G. Johnson, and S. Krivov. 2009. ARIES (Artificial Intelligence for Ecosystem Services): A new tool for ecosystem services assessment, planning, and valuation. Proceedings of the 11th Annual BIOECON Conference on Economic Instruments to Enhance the Conservation and Sustainable Use of Biodiversity Venice, Italy, September, 2009.

Vitousek, P. M., J. D. Aber, R. W. Howarth, G. E. Likens, P. A. Matson, D. W. Schindler, W. H. Schlesinger, and D. G. Tilman. 1997. Human alteration of the global nitrogen cycle: sources and consequences. Ecological Applications 7:737-750.

Ward, M., S. Mark, K. Cantor, D. Weisenburger, and A. Correa-Villasenor. 2000. Non-Hodgkin's lymphoma and nitrate in drinking water. Journal of Epidemiology and Community Health 54:772-773.

Ward, M., S. Mark, K. Cantor, D. Weisenburger, A. CorreaVillasenor, and S. Zahm. 1996. Drinking water nitrate and the risk of non-Hodgkin's lymphoma. Epidemiology 7:465-471.

Ward, M. H., B. Kilfoy, R. Sinha, A. R. Hollenbeck, A. Schatzkin, and A. Cross. 2011. Ingestion of Nitrate and Nitrite and Risk of Stomach Cancer in the NIH-AARP Diet and Health Study. Epidemiology 22:S107-S108.

Weyer, P. J., J. R. Kantamneni, X. Lu, M. H. Ward, and J. R. Cerhan. 2008. Nitrate Ingestion from Drinking Water and Diet and Cancer Risk. Epidemiology 19:S55-S55.

Wick, K., C. Heumesser, and E. Schmid. 2012. Groundwater nitrate contamination: Factors and indicators. Journal of Environmental Management 111:178-186.

Wilson, M. A., S. R. Carpenter. 1999. Economic valuation of freshwater ecosystem services in the United States: 1971-1997. Ecological Applications 9:772-783.

Wood, S. A., A. D. Guerry, J. M. Silver, and M. Lacayo. 2013. Using social media to quantify nature-based tourism and recreation. Scientific Reports 3:2976.

Wright, C. K., M. C. Wimberly. 2013. Recent land use change in the Western Corn Belt threatens grasslands and wetlands. Proceedings of the National Academy of Sciences 110:4134-4139.

Wu, Y., S. Liu. 2012. Impacts of biofuels production alternatives on water quantity and quality in the Iowa River Basin. Biomass and Bioenergy 36:182-191.

Appendices

Appendix 1.1 References for case studies, research papers, models, or illustrative examples to support application of the water quality valuation template presented in Figure 3.

Lake Recreation

Relationship between phosphorus loading and lake water clarity

1. Canfield Jr DE & Bachmann RW (1981) Prediction of total phosphorus concentrations, chlorophyll a, and secchi depths in natural and artificial lakes. Can J Fish Aquat Sci 38: 414-423.

2. Carlson RE (1977) A trophic state index for lakes. Limnol Oceanogr 361-369.

3. Dillon P & Rigler F (1974) The phosphorus-chlorophyll relationship in lakes. Limnol Oceanogr 767-773.

4. Heiskary SA & Walker Jr WW (1988) Developing phosphorus criteria for Minnesota lakes. Lake Reserv Manage 4: 1-9.

5. Smith VH & Shapiro J (1981) Chlorophyll-phosphorus relations in individual lakes. their importance to lake restoration strategies. Environ Sci Technol 15: 444-451.

6. Sterner RW (2008) On the phosphorus limitation paradigm for lakes. Int Rev Hydrobiol 93: 433-445.

7. Vollenweider RA (1970) Scientific fundamentals of the eutrophication of lakes and flowing waters, with particular reference to nitrogen and phosphorus as factors in eutrophication. OECD Report, September 1970.159 P.

8. Vollenweider RA (1976) Advances in defining critical loading levels for phosphorus in lake eutrophication. Mem Ist Ital Idrobiol 33: 53-83.

9. Wagner T, Soranno PA, Webster KE & Cheruvelil KS (2011) Landscape drivers of regional variation in the relationship between total phosphorus and chlorophyll in lakes. Freshwat Biol. 56:1811-1824.

10. Bryhn AC, L Hakanson (2007) A comparison of predictive phosphorus load-concentration models for lakes. Ecosystems 10:1084-1099.

11. Nurnberg GK (2009) Assessing internal phosphorus load - Problems to be solved. Lake and Reserv. Manag. 25:419-432.

Valuation of changes in water quality: Recreational demand models

12. Bockstael NE, Hanemann WM & Kling CL (1987) Estimating the value of water quality improvements in a recreational demand framework. Water Resour Res 23: 951-960.

13. Bockstael NE, McConnell KE & Strand I (1989) Measuring the benefits of improvements in water quality: The Chesapeake Bay. Mar Resour Econ 6:1-18.

14. Bockstael N & McConnell K (2007) Environmental and resource valuation with revealed preferences: A theoretical guide to empirical models. Environmental and Resource Valuation with Revealed Preferences: A Theoretical Guide to Empirical Models 7: 1-375.

15. Parsons GR & Kealy MJ (1992) Randomly drawn opportunity sets in a random utility model of lake recreation. Land Econ 68: 93-106.

16. Egan KJ, Herriges JA, Kling CL & Downing JA (2009) Valuing water quality as a function of water quality measures. Am J Agric Econ 91: 106-123.

17. Phaneuf DJ (2002) A random utility model for total maximum daily loads: Estimating the benefits of watershed-based ambient water quality improvements. Water Resour Res 38: 1-11.

18. Phaneuf DJ & Smith VK (2005) Recreation demand models. Handbook of Environmental Economics 2: 671-761.

19. Phaneuf DJ, Kling CL & Herriges JA (2000) Estimation and welfare calculations in a generalized corner solution model with an application to recreation demand. Rev Econ Stat 82: 83-92.

20. Huang J, Haab T & Whitehead J (1997) Willingness to pay for quality improvements: Should revealed and stated preference data be combined? J Environ Econ Manage 34: 240-255.

21. Vesterinen J, Pouta E, Huhtala A & Neuvonen M (2010) Impacts of changes in water quality on recreation behavior and benefits in Finland. J Environ Manage 91: 984-994.

Valuation of changes in water quality: Willingness to pay for recreation (Contingent valuation)

22. Carson RT & Mitchell RC (1993) The value of clean water: The public's willingness to pay for boatable, fishable, and swimmable quality water. Water Resources Research 29:2445-2454.

23. Viscusi WK, Huber J & Bell J (2008) The economic value of water quality. Environ Resour Econ 41: 169-187.

24. Magat WA, Huber J, Viscusi WK & Bell J (2000) An iterative choice approach to valuing clean lakes, rivers, and streams. J Risk Uncertainty 21: 7-43.

25. Johnston R, et al (2005) Systematic variation in willingness to pay for aquatic resource improvements and implications for benefit transfer: A meta-analysis. Canadian Journal of Agricultural Economics-Revue Canadienne D Agroeconomie 53: 221-248.

26. Van Houtven G, Powers J & Pattanayak SK (2007) Valuing water quality improvements in the United States using meta-analysis: Is the glass half-full or half-empty for national policy analysis? Resource and Energy Economics 29: 206-228.

27. Johnston RJ, Ranson MH, Besedin EY & Helm EC (2006) What determines willingness to pay per fish? A meta-analysis of recreational fishing values. Mar Resour Econ 21: 1-32.

Valuation of changes in lake water clarity: Hedonic pricing models

28. Steinnes D (1992) Measuring the economic value of water-quality: The case of lakeshore land. Ann Reg Sci 26: 171-176.

29. Epp D & Alani K (1979) Effect of water-quality on rural non-farm residential property values. Am J Agric Econ 61: 529-534.

30. Michael H, Boyle K & Bouchard R (2000) Does the measurement of environmental quality affect implicit prices estimated from hedonic models? Land Econ 76: 283-298.

31. Poor PJ, Pessagno KL & Paul RW (2007) Exploring the hedonic value of ambient water quality: A local watershed-based study. Ecol Econ 60: 797-806.

32. Poor P, Boyle K, Taylor L & Bouchard R (2001) Objective versus subjective measures of water clarity in hedonic property value models. Land Econ 77: 482-493.

33. Anderson ST & West SE (2006) Open space, residential property values, and spatial context. Regional Science and Urban Economics 36: 773-789.

34. Cho S, Roberts RK & Kim SG (2011) Negative externalities on property values resulting from water impairment: The case of the pigeon river watershed. Ecol Econ 70: 2390-2399.

35. Phaneuf DJ, Smith VK, Palmquist RB & Pope JC (2008) Integrating property value and local recreation models to value ecosystem services in urban watersheds. Land Econ 84: 361-381.

36. Walsh PJ, Milon JW & Scrogin DO (2011) The spatial extent of water quality benefits in urban housing markets. Land Econ 87: 628-644.

37. Loomis J & Feldman M (2003) Estimating the benefits of maintaining adequate lake levels to homeowners using the hedonic property method. Water Resour Res 39: 1259.

38. Leggett C & Bockstael N (2000) Evidence of the effects of water quality on residential land prices. J Environ Econ Manage 39: 121-144.

General reviews of water quality valuation models and methods

39. Wilson MA & Carpenter SR (1999) Economic valuation of freshwater ecosystem services in the United States: 1971-1997. Ecol Appl 9: 772-783.

40. Dumas CF, et al (2005) Measuring the economic benefits of water quality improvement with benefit transfer: An introduction for non-economists 47: 53.

41. Koteen J, Alexander SJ & Loomis JB (2002) Evaluating benefits and costs of changes in water quality. USDA Forest Service General Technical Report Pacific Northwest.

42. Mendelsohn R & Olmstead S (2009) The economic valuation of environmental amenities and disamenities: Methods and applications. Annual Review of Environment and Resources 34: 325-347.

43. Dodds WK, et al (2009) Eutrophication of U.S. freshwaters: Analysis of potential economic damages. Environ Sci Technol 43: 12-19.

44. Olmstead SM (2010) The economics of water quality. Review of Environmental Economics and Policy 4: 44-62.

45. Griffiths C, et al (2012) U.S. Environmental Protection Agency valuation of surface water quality improvements. Review of Environmental Economics and Policy 6: 130-146.

46. Iovanna R & Griffiths C (2006) Clean water, ecological benefits, and benefits transfer: A work in progress at the US EPA. Ecol Econ 60: 473-482.

47. Freeman,A.Myrick,,III (2006) Valuing environmental health effects - an economic perspective. Environ Resour Econ 34: 347-363.

48. Corrigan JR, Egan KJ & Downing JA (2007) Aesthetic values of lakes and rivers. Working Papers. Department of Economics, Kenyon College.

49. Brauman KA, Daily GC, Duarte TK & Mooney HA (2007) The nature and value of ecosystem services: An overview highlighting hydrologic services. Annu.Rev.Environ.Resour. 32: 67-98.

Clean drinking water

Avoided treatment costs for nitrate in drinking water

50. Hernandez-Sancho F, Senante MM & Sala-Garrido R (2009) Environmental benefits of wastewater treatment: An economic valuation. Risk Management of Water Supply and Sanitation Systems 251-260.

51. Hanley N (1990) The economics of nitrate pollution. Eur Rev Agric Econ 17: 129-151.

52. Kapoor A & Viraraghavan T (1997) Nitrate removal from drinking water - review. Journal of Environmental Engineering-ASCE 123: 371-380.

53. Moore E, et al (2011) The human costs of nitrate-contaminated drinking water in the San Joaquin Valley. Pacific Institute Oakland, CA.

Avoided treatment costs for nitrate in groundwater wells

54. Lewandowski A, Montgomery B, Rosen C & Moncrief J (2008) Groundwater nitrate contamination costs: A survey of private well owners. J Soil Water Conserv 63: 153-161.

55. Ledoux E. Gomez E, Monget JM, Viavattene C, Viennot P, Ducharne A, Benoit M, Mignolet C, Schott C, Mary B (2007) Agriculture and groundwater nitrate contamination in the Seine basin. The STICS–MODCOU modeling chain. Sci of the Total Envir 375:33-47.

Health risks associated with nitrate in drinking water

56. Ward MH, et al (2011) Ingestion of nitrate and nitrite and risk of stomach cancer in the NIH-AARP diet and health study. Epidemiology 22: S107-S108.

57. Ward MH, et al (2010) Nitrate intake and the risk of thyroid cancer and thyroid disease. Epidemiology 21: 389-395.

58. Weyer PJ, Kantamneni JR, Lu X, Ward MH & Cerhan JR (2008) Nitrate ingestion from drinking water and diet and cancer risk. Epidemiology 19: S55-S55.

59. Ward MH, Heineman EF, Markin RS & Weisenburger DD (2008) Adenocarcinoma of the stomach and esophagus and drinking water and dietary sources of nitrate and nitrite. International Journal of Occupational and Environmental Health 14: 193-197.

60. Ward MH, Rusiecki JA, Lynch CF & Cantor KP (2007) Nitrate in public water supplies and the risk of renal cell carcinoma. Cancer Causes & Control 18: 1141-1151.

61. Ward MH, Weyer P, Wang A & Cerhan JR (2007) Nitrate from drinking water and diet and thyroid disorders and thyroid cancer among women. Epidemiology 18: S169-S169.

62. Ward M, Cantor K, Cerhan J, Lynch C & Hartge P (2004) Nitrate in public water supplies and risk of cancer: Results from recent studies in the Midwestern United States. Epidemiology 15: S214-S214.

63. Ward M, Cantor K, Riley D, Merkle S & Lynch C (2003) Nitrate in public water supplies and risk of bladder cancer. Epidemiology 14: 183-190.

64. Weyer P, et al (2001) Municipal drinking water nitrate level and cancer risk in older women: The Iowa women's health study. Epidemiology 12: 327-338.

65. Townsend AR, et al (2003) Human health effects of a changing global nitrogen cycle. Frontiers in Ecology and the Environment 1: 240-246.

66. Camargo JA & Alonso A (2006) Ecological and toxicological effects of inorganic nitrogen pollution in aquatic ecosystems: A global assessment. Environ Int 32: 831-849.

67. Bouchard D, Williams M & Surampalli R (1992) Nitrate contamination of groundwater - sources and potential health-effects. Journal American Water Works Association 84: 85-90.

Valuation of health risks due to drinking water quality

68. van Grinsven HJM, Rabl A & de Kok TM (2010) Estimation of incidence and social cost of colon cancer due to nitrate in drinking water in the EU: A tentative cost-benefit assessment. Environ Health 9: 58.

69. Viscusi W & Aldy J (2003) The value of a statistical life: A critical review of market estimates throughout the world. J Risk Uncertainty 27: 5-76.

70. Aldy JE & Viscusi WK (2008) Adjusting the value of a statistical life for age and cohort effects. Rev Econ Stat 90: 573-581.

71. Kuchler R & Golan E (1999) Assigning values to life: Comparing methods for valuing health. Food and Rural Economics Division, Economic Research Service, USDA. Agricultural Economic Report No. 784.

Commercial fisheries

Relationship between nutrient loading and coastal fish and shellfish productivity

72. Breitburg DL, Hondorp DW, Davias LA & Diaz RJ (2009) Hypoxia, nitrogen, and fisheries: Integrating effects across local and global landscapes. Annual Review of Marine Science 1: 329-349.

73. Huang L & Smith MD (2011) Management of an annual fishery in the presence of ecological stress: The case of shrimp and hypoxia. Ecol Econ 70: 688-697.

74. Huang L, Smith MD & Craig JK (2010) Quantifying the economic effects of hypoxia on a fishery for brown shrimp farfantepenaeus aztecus. Marine and Coastal Fisheries: Dynamics, Management, and Ecosystem Science 2: 232-248.

75. Diaz RJ & Rosenberg R (2011) Introduction to environmental and economic consequences of hypoxia. Int J Water Resour Dev 27: 71-82.

Coastal recreation

Relationship between nutrient loading and algal blooms

76. Cloern J (2001) Our evolving conceptual model of the coastal eutrophication problem. Marine Ecology-Progress Series 210: 223-253.

77. Heisler J, et al (2008) Eutrophication and harmful algal blooms: A scientific consensus. Harmful Algae 8: 3-13.

78. Anderson DM, Glibert PM & Burkholder JAM (2002) Harmful algal blooms and eutrophication: Nutrient sources, composition, and consequences. Estuaries and Coasts 25: 704-726.

79. Bricker SB, et al (2008) Effects of nutrient enrichment in the nation's estuaries: A decade of change. Harmful Algae 8: 21-32.

80. Hudnell HK (2010) The state of US freshwater harmful algal blooms assessments, policy and legislation. Toxicon 55: 1024-1034.

81. Garnier J, et al (2010) N: P: Si nutrient export ratios and ecological consequences in coastal seas evaluated by the ICEP approach. Global Biogeochem.Cycles 24: GB0A05.

Valuation models for coastal recreation

82. Hoagland P, Anderson D, Kaoru Y & White A (2002) The economic effects of harmful algal blooms in the United States: Estimates, assessment issues, and information needs. Estuaries and Coasts 25: 819-837.

83. Larkin SL & Adams CM (2007) Harmful algal blooms and coastal business: Economic consequences in Florida. Soc Nat Resour 20: 849-859.

84. Hoagland P & Scatasta S (2006) The economic effects of harmful algal blooms. Ecology of Harmful Algae 391-402.

85. Freeman AM (1995) The benefits of water quality improvements for marine recreation: A review of the empirical evidence. Mar Resour Econ 10: 385-406.

86. Pendleton L, Martin N & Webster D (2001) Public perceptions of environmental quality: A survey study of beach use and perceptions in Los Angeles county. Mar Pollut Bull 42: 1155-1160.

Safe contact with recreation water

Relationship between nutrient loading and disease or irritation

87. Johnson P & Townsend A (2008) Nutrient enrichment in aquatic ecosystems and emergence of human and animal diseases. Epidemiology 19: S56-S56.

88. Johnson PTJ, et al (2010) Linking environmental nutrient enrichment and disease emergence in humans and wildlife. Ecol Appl 20: 16-29.

89. Falconer I (1999) An overview of problems caused by toxic blue-green algae (cyanobacteria) in drinking and recreational water. Environ Toxicol 14: 5-12.

90. Wade TJ, et al (2010) Rapidly measured indicators of recreational water quality and swimming-associated illness at marine beaches: A prospective cohort study. Environ Health 9: 66.

91. Wade T, et al (2006) Rapidly measured indicators of recreational water quality are predictive of swimming-associated gastrointestional illness. Environ Health Perspect 114: 24-28.

92. Seyfried P, Tobin R, Brown N & Ness P (1985) A prospective-study of swimming-related illness, morbidity and the microbiological quality of water. Am J Public Health 75: 1071-1075.

93. Cabelli V (1989) Swimming-associated illness and recreational water-quality criteria. Water Science and Technology 21: 13-21.

Valuation of impacts or avoidance behaviors associated with aquatic pest and parasites

94. Leshem E, Maor Y, Meltzer E, Assous M & Schwartz E (2008) Acute schistosomiasis outbreak: Clinical features and economic impact. Clinical Infectious Diseases 47: 1499-1506.

95. Dwight R, Fernandez L, Baker D, Semenza J & Olson B (2005) Estimating the economic burden from illnesses associated with recreational coastal water pollution - A case study in Orange County, California. J Environ Manage 76: 95-103.

Coldwater angling

Relationship between stream temperature and trout populations

96. Isaak DJ & Hubert WA (2004) Nonlinear response of trout abundance to summer stream temperatures across a thermally diverse montane landscape. Trans Am Fish Soc 133: 1254-1259.

97. Wenger SJ, et al (2011) Role of climate and invasive species in structuring trout distributions in the interior Columbia River Basin, USA. Can J Fish Aquat Sci 68: 988-1008.

98. Isaak D & Hubert W (2001) A hypothesis about factors that affect maximum summer stream temperatures across montane landscapes. J Am Water Resour Assoc 37: 351-366.

99. Wehrly KE, Wang L & Mitro M (2007) Field-based estimates of thermal tolerance limits for trout: Incorporating exposure time and temperature fluctuation. Trans Am Fish Soc 136: 365-374.

100. Creque SM, Rutherford ES & Zorn TG (2005) Use of GIS-derived landscape-scale habitat features to explain spatial patterns of fish density in Michigan rivers. N Am J Fish Manage 25: 1411-1425.

101. Steen PJ, Zorn TG, Seelbach PW & Schaeffer JS (2008) Classification tree models for predicting distributions of Michigan stream fish from landscape variables. Trans Am Fish Soc 137: 976-996.

Valuation of changes in trout abundance or habitat suitability

102. McKean JR, Johnson D & Taylor RG (2010) Willingness-to-pay for steelhead trout fishing: Implications of two-step consumer decisions with short-run endowments. Water Resour Res 46: W09523.

103. Dalton RS, Bastian CT, Jacobs JJ & Wesche TA (1998) Estimating the economic value of improved trout fishing on wyoming streams. N Am J Fish Manage 18: 786-797.

104. Harris (2010) Trout Fishing in 2006: A Demographic Description and Economic Analysis, Addendum to the 2006 National Survey of Fishing, Hunting, and Wildlife-Associated Recreation. Report 2006-6.

Avoided sedimentation

Valuation of sediment deposition

105. Hansen L, Breneman V, Davison C, Dicken C (2002) The cost of soil erosion to downstream navigation. J of Soil and Water Cons 57:205-212.

106. Hansen L & Ribaudo M (2008) Economic measures of soil conservation benefits: Regional values for policy assessment. USDA Economic Research Service Technical Bulletin No. 1922.

107. Hansen L & Hellerstein D (2007) The value of the reservoir services gained with soil conservation. Land Econ 83: 285-301.

108. Southgate D & Macke R (1989) The downstream benefits of soil conservation in 3rd-world hydroelectric watersheds. Land Econ 65: 38-48.

109. Sude B, et al (2011) New approach for evaluation of a watershed ecosystem service for avoiding reservoir sedimentation and its economic value: A case study from Ertan reservoir in Yalong River, China. Applied and Environmental Soil Science 2011: 576947.

110. U.S. Army Corps of Engineers (1999) Civil works digital project notebook (DPN). http://crunch.tec.army.mil/dpn/webpages/dpn_intro.cfm

Safe drinking water: DOC

111. Pellerin BA, Hernes PJ, Saraceno J, Spencer RGM & Bergamaschi BA (2010) Microbial degradation of plant leachate alters lignin phenols and trihalomethane precursors. J Environ Qual 39: 946-954.

112. Chow AT, Dahlgren RA & Harrison JA (2007) Watershed sources of disinfection byproduct precursors in the Sacramento and San Joaquin Rivers, California. Environ Sci Technol 41: 7645-7652.

113. Engelage SK, Stringfellow WT & Letain T (2009) Disinfection byproduct formation potentials of wetlands, agricultural drains, and rivers and the effect of biodegradation on trihalomethane precursors. J Environ Qual 38: 1901-1908.

114. Camel V & Bermond A (1998) The use of ozone and associated oxidation processes in drinking water treatment. Water Res 32: 3208-3222.

115. Legrini O, Oliveros E & Braun A (1993) Photochemical processes for water-treatment. Chem Rev 93: 671-698.

116. Schlichter B, Mavrov V, Erwe T & Chmiel H (2004) Regeneration of bonding agents loaded with heavy metals by electrodialysis with bipolar membranes. J Membr Sci 232: 99-105.

117. Pinney M, Westerhoff P & Baker L (2000) Transformations in dissolved organic carbon through constructed wetlands. Water Res 34: 1897-1911.

118. Hsu C, Jeng W, Chang R, Chien L & Han B (2001) Estimation of potential lifetime cancer risks for trihalomethanes from consuming chlorinated drinking water in Taiwan. Environ Res 85: 77-82.

119. U.S. Environmental Protection Agency (2011) Drinking water contaminants: National primary drinking water regulations.

120. Desimone L, Hamilton P & Gilliom R (2009) Quality of water from domestic wells in prinicpal aquifers of the United States, 1991-2004: Overview of major findings. USGS National Water Quality Assessment Program. Scientific Investigations Report 2008-5227.

Safe drinking and/or contact with water: Toxins

Toxin exposure and human health

121. Easter KW & Konishi Y (2006) What are the economic health costs of non-action in controlling toxic water pollution? Water Resources Development 22: 529-541.

122. Jamieson R, Gordon R, Sharples K, Stratton G & Madani A (2002) Movement and persistence of fecal bacteria in agricultural soils and subsurface drainage water: A review. Canadian Biosystems Engineering 44: 1.1-1.9.

123. Rusin P, Rose J, Haas C & Gerba C (1997) Risk assessment of opportunistic bacterial pathogens in drinking water. Reviews of Environmental Contamination and Toxicology 152:58-83.

124. Focazio MJ, et al (2008) A national reconnaissance for pharmaceuticals and other organic wastewater contaminants in the United States - Untreated drinking water sources. Sci Total Environ 402: 201-216.

125. Funari E & Testai E (2008) Human health risk assessment related to cyanotoxins exposure. Crit Rev Toxicol 38: 97-125.

126. Codd G, Morrison L & Metcalf J (2005) Cyanobacterial toxins: Risk management for health protection. Toxicol Appl Pharmacol 203: 264-272.

127. Codd G (2000) Cyanobacterial toxins, the perception of water quality, and the prioritisation of eutrophication control. Ecol Eng 16: 51-60.

128. de Figueiredo D, Azeiteiro U, Esteves S, Goncalves F & Pereira M (2004) Microcystin-producing blooms - a serious global public health issue. Ecotoxicol Environ Saf 59: 151-163.

129. Tchounwou P, Patlolla A & Centeno J (2003) Carcinogenic and systemic health effects associated with arsenic exposure - A critical review. Toxicol Pathol 31: 575-588.

130. Ratnaike R (2003) Acute and chronic arsenic toxicity. Postgrad Med J 79: 391-396.

131. Rao P, Gupta N, Bhaskar A & Jayaraj R (2002) Toxins and bioactive compounds from cyanobacteria and their implications on human health. J Environ Biol 23: 215-224.

132. Kolpin D, et al (2002) Pharmaceuticals, hormones, and other organic wastewater contaminants in US streams, 1999-2000: A national reconnaissance. Environ Sci Technol 36: 1202-1211.

133. Basu A, Mahata J, Gupta S & Giri A (2001) Genetic toxicology of a paradoxical human carcinogen, arsenic: A review. Mutat Res - Rev Mut Res 488: 171-194.

134. Zahm S & Ward M (1998) Pesticides and childhood cancer. Environ Health Perspect 106: 893-908.

135. Cantor K (1997) Drinking water and cancer. Cancer Causes & Control 8: 292-308.

136. Pontius F, Brown K & Chen C (1994) Health implications of arsenic in drinking-water. Journal American Water Works Association 86: 52-63.

Toxins exposure via consumption of fish and/or shellfish

137. Ibelings BW & Chorus I (2007) Accumulation of cyanobacterial toxins in freshwater "seafood" and its consequences for public health: A review. Environmental Pollution 150: 177-192.

138. Hylander LD & Goodsite ME (2006) Environmental costs of mercury pollution. Sci Total Environ 368: 352-370.

Valuation of changes in human health due to unsafe contact or consumption

139. Konishi Y & Coggins JS (2006) Value of information and averting behavior: The case of toxic water contamination. Selected paper presented at the AAEA Annual Meeting, Long Beach, California.

140. Svrcek C & Smith D (2004) Cyanobacteria toxins and the current state of knowledge on water treatment options: A review. Journal of Environmental Engineering and Science 3: 155-185.

141. Pretty J, et al (2000) An assessment of the total external costs of UK agriculture. Agricultural Systems 65: 113-136.

142. Hitzfeld B, Hoger S & Dietrich D (2000) Cyanobacterial toxins: Removal during drinking water treatment, and human risk assessment. Environ Health Perspect 108: 113-122.

143. Hoeger S, Hitzfeld B & Dietrich D (2005) Occurrence and elimination of cyanobacterial toxins in drinking water treatment plants. Toxicol Appl Pharmacol 203: 231-242.

144. Revesz R (1999) Environmental regulation, cost-benefit analysis, and the discounting of human lives. Columbia Law Rev 99: 941-1017.

Non-use value

Research on non-use values related to water quality

145. Johnston R, Besedin E & Wardwell R (2003) Modeling relationships between use and nonuse values for surface water quality: A meta-analysis. Water Resour Res 39: 1363.

146. Sanders L, Walsh R & Loomis J (1990) Toward empirical estimation of the total value of protecting rivers. Water Resour Res 26: 1345-1357.

147. Sutherland R & Walsh R (1985) Effect of distance on the preservation value of water-quality. Land Econ 61: 281-291.

148. Bateman I, Cole M, Georgiou S & Hadley D (2006) Comparing contingent valuation and contingent ranking: A case study considering the benefits of urban river water quality improvements. J Environ Manage 79: 221-231.

149. Silberman J, Gerlowski D & Williams N (1992) Estimating existence value for users and nonusers of New Jersey beaches. Land Econ 68: 225-236.

150. Johnston R, Opaluch J, Magnusson G & Mazzotta M (2005) Who are resource nonusers and what can they tell us about nonuse values? Decomposing user and nonuser willingness to pay for coastal wetland restoration. Water Resour Res 41: W07017.

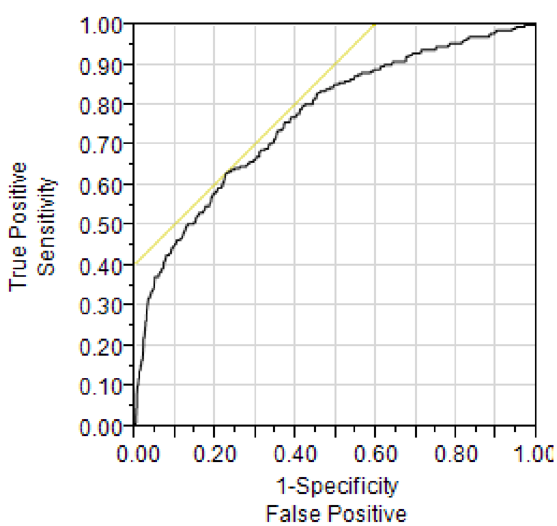
151. Brown TC (1993) Measuring nonuse value: A comparison of recent contingent valuation studies, W-133 Sixth Interim Rep., Dep. of Agric. and Appl. Econ., Univ. of Ga., Athens.

Appendix 2.1

Evaluation of model fit

I used two statistical tests to evaluate the predictive ability of the multivariate logistic regression model. The Lack of Fit or Goodness of Fit test addresses whether more complex terms are needed in the current model or if there appears to be enough information with the existing variables. The null hypothesis for this test is that the model fits the data, therefore a higher p-value indicates a well-calibrated model. For both the 4ppm and 10ppm logistic regression models, the lack of fit p-value was 1.0 indicating that there is little to be gained by introducing additional variables to the model.

I also used Receiver Operating Characteristic (ROC) curves to evaluate each model (Figure 2.1). Curves which are further to the left and higher on the vertical axis have greater predictive capacity. The accuracy of the model is represented as the tradeoff between specificity or the rate of false positives and sensitivity, which is the rate of true positives. Accuracy is measured by the area under the ROC curve (AUC), where an area of 1 represents a perfect model and an area of .5 represents zero predictability. The AUC estimates for the 4 ppm and 10 ppm models are 0.77 and 0.86, respectively, represent fair to good predictive power and meet or exceed AUC estimates from previous groundwater models (Gurdak and Qi 2012).



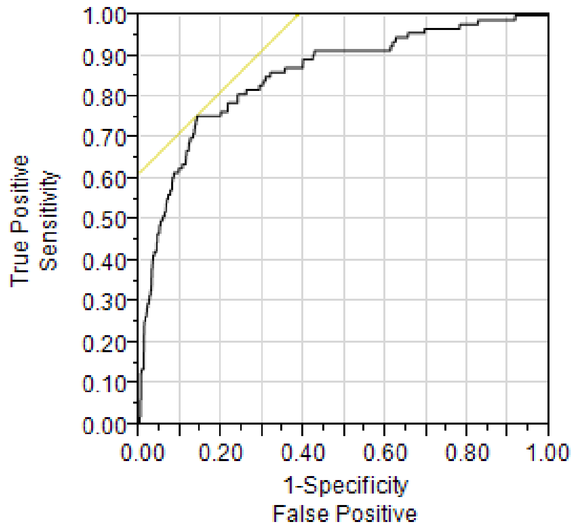


Figure 2.1: ROC curves for the 4ppm model (top) and 10ppm model (below). Axes represent the rate of false positives (specificity) and true positives (sensitivity). The greater the area under the curve, the better the predictive ability of the model. The straight line is drawn at a 45 degree angle tangent to the ROC Curve and is useful in identifying the probability threshold which balances the frequency of false negatives and false positives. AUC 4ppm = .77, AUC for 10ppm = 0.86

Appendix 2.2

Selecting a probability threshold to apply to the logistic regression model

Figure 2.2 plots a range of probability thresholds based on how these values influence the total error rate and rate of positive detection. For the 4 ppm model, a probability threshold of 0.27 predicted 98% of the total number of contaminated wells (true positives + false positives/total number of observed positives), with a 15% total error rate (number of false positives + the number of false negatives/total samples). The lowest total error rate was at a cutoff probability of 0.36, with 12% error. At this level, the model estimates only 52% of the total number of actual contaminated wells (Chapter 1, Figure 5). For the 10 ppm model, a 0.23 cutoff predicted 100% of the total number of actual contaminated wells and yielded a 6% error rate. Minimizing total error rate to the lowest value of 5% selects a cutoff of 0.39 which predicts only 44% of total contamination (Chapter 1, Figure 5). The penalty of raising the probability cutoff to positive rate detection was greater than the penalty to total error, therefore I selected probability cutoffs based on values just above the 100% threshold (0.28 for the 4 ppm model and 0.24 for the 10 ppm) which slightly under-predicts the total number of contaminated wells. Note that these thresholds are greater (more conservative) than the probability cutoffs identified in the ROC curves (Appendix 2.1) which represent an equal balance between the frequency of false negatives and false positives. The 45 degree angle tangent to the ROC curve representing this point for the 4 ppm model corresponds with a 0.16 cutoff and a 0.08 cutoff for the 10 ppm model.

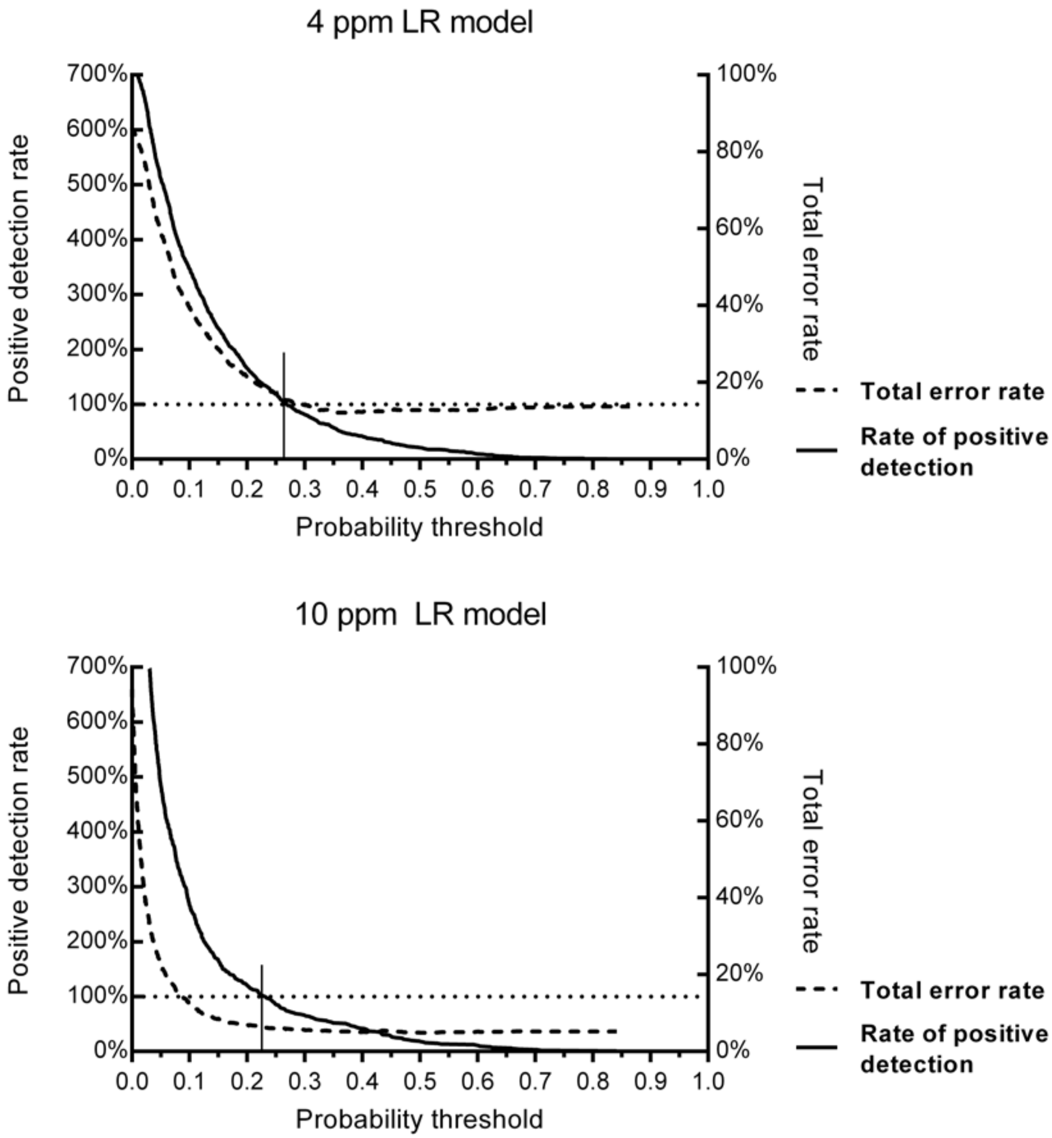


Figure 2.2: Plot of the total error rate and the rate of positive detection (correct number of contaminated wells) for each probability threshold. The vertical line marks the threshold where the model correctly predicts the total number of contaminated wells.

Appendix 3.1

For each state, I fit each explanatory variable in a bi-variate regression with photo-user-days per lake as the response variable. Significance and dwerection (+/-) of the relationships are presented below for Iowa and Minnesota lakes, where nd = no data ad ns = non-significant where $p > 0.10$.

Bivariate regressions for lake attributes and visitation for Minnesota and Iowa lakes

	Minnesota	**Iowa**
	n = 2120 lakes	n = 138 lakes
Lake size (acres)	<0.0001 (+)	<0.0001 (+)
Lake clarity (m)	ns	0.0015 (+)
Lake depth (m)	<0.0001 (+)	<0.0001 (+)
Chlorophyll (ug/L)	ns	0.0410 (-)
Total phosphorus (ug/L)	ns	0.0622 (-)
Near-lake population (people)	<0.0001 (+)	ns
Lake cyanobacteria biomass (mg/L)	nd	0.0125 (+)
Lake phytoplankton biomass (mg/L)	nd	0.0167 (+)
Lake temperature (C)	nd	0.0745 (-)
State Park	ns	nd
Boat launch	<0.0001 (+)	0.0390 (+)
Number of ramps	<0.0001 (+)	nd
Number of docks	<0.0001 (+)	nd
Number of toilets	<0.0001 (+)	nd
Number of ADA facilities	<0.0001 (+)	nd
Percent littoral area	ns	nd
Aquatic invasive species (1 = present)	<0.0001 (+)	No data
Boundary waters lake	ns	-

Appendix 3.2

Pairwise correlations of explanatory variables evaluated in regression models for visitation and travel time. Data represent all lakes in Minnesota and Iowa with water quality attributes. Red values (bold) are correlations greater than 0.5, blue values (italics) are for correlations greater than 0.25. As expected, lake clarity is negatively correlated with chlorophyll and total phosphorus and positively correlated with lake depth.

Pairwise correlations of lake explanatory variables for combined lake data

	Lake size (acres)	Lake clarity (m)	Lake depth (m)	Chlorophyll (ug/L)	Total phosphorus (ug/L)	Near lake population (no. people in 80 km radius)
Lake size (acres)		-0.01	0.06	-0.03	-0.01	-0.05
Lake clarity (m)	-0.01		**0.60**	**-0.55**	*-0.46*	*-0.33*
Lake depth (m)	0.06	**0.60**		*-0.38*	*-0.32*	-0.18
Chlorophyll (ug/L)	-0.03	**-0.55**	*-0.38*		**0.64**	*0.27*
Total phosphorus (ug/L)	-0.01	*-0.46*	*-0.32*	**0.64**		0.21
Near lake population (no. people in 80 km radius)	-0.05	*-0.33*	-0.18	*0.27*	0.21	