Measuring Nutrient Reduction Benefits for Policy Analysis Using Linked Non-Market Valuation and Environmental Assessment Models – An Interim Report On Water Quality Modeling

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Abstract

This document summarizes the first year of work on the project *Measuring Nutrient Reduction Benefits for Policy Analysis Using Linked Non-Market Valuation and Environmental Assessment Models*. The project's overall objective is to provide an integrated protocol that will assist state water quality managers in one aspect of their efforts to set numeric ambient nutrient pollution standards for surface water. The specific focus is on measuring the dollar-denominated benefits of nutrient reductions as they pertain to recreation and aesthetic services. To accomplish this task a mechanism is needed that links measured nutrient pollution (i.e. ambient nitrogen, phosphorous, etc.) to a qualitative ranking of water quality, which can then be tied to an economic model of valuation. In this technical document we describe Module 1 in our project, which centers on 1) estimating a function that maps measures of nutrient pollution to an ordinal ranking of water quality, and 2) using this function to predict surface water rankings in individual lakes across our study area.

To characterize the relationship between objectively measured water quality parameters and a subjective ordinal ranking we rely on expert elicitation. Specifically, a panel of water quality experts was presented with values for an array of water quality parameters and were asked to judge how water bodies with given measures would rank according to a predefined scale. Multiple responses to different parameter values were then used to quantify the mapping from objective measures to subjective ranking. We investigate two different statistical models for fitting a functional relationship, and find robustness in model performance and predictions across the two methods. We find that chlorophyll *a* and Secchi depth are the strongest predictors of eutrophication levels, followed by total phosphorus and total nitrogen.

We use our models to predict water quality rankings (trophic state levels) at representative lakes and reservoirs in North Carolina and South Carolina. Our demonstrations

suggest the research completed in Module 1 is quite successful and is on track for use in the general protocol proposed in our project. This statement, however, is contingent on the availability of sufficient monitoring station measurements for the reservoirs of interest - particularly for Secchi depth and chlorophyll *a*, which we found to be particularly sparse in our South Carolina demonstrations.

We close our discussion by providing comments on our models' spatial transferability, general limitations and sources of uncertainty, and further research and data gathering that could enhance the overall protocol that we are proposing in this project.

Contents

1) INTRODUCTION

This document summarizes the first year of work on the project *Measuring Nutrient Reduction Benefits for Policy Analysis Using Linked Non-Market Valuation and Environmental Assessment Models*. The project's overall objective is to provide an integrated protocol for assisting state water quality managers in one aspect of their efforts to set numeric ambient nutrient pollution standards for surface water. The specific focus is on measuring the dollar-denominated benefits of nutrient reductions as they pertain to recreation and aesthetic services. For this a mechanism is needed that links measured nutrient pollution (i.e. ambient nitrogen, phosphorous, etc.) to a qualitative ranking of water quality, which can then be tied to an economic model of valuation. Our objective in this technical document is to describe research (module 1 in our project) centered on the first part of this: estimation of a function mapping measures of nutrient pollution to an ordinal ranking of quality, and its use for predicting surface water rankings across our study area.

To provide context for this effort we first describe the motivation for the project and its overall structure. In 2007 EPA's Office of Water solicited proposals for research that would "...aid States in their attempts to estimate monetary benefits associated with nutrient reductions as they strive to adopt numeric nutrient criteria into their State water quality standards" (EPA-OW, 2007, p.2). The solicitation was motivated by the desire among state and federal managers to establish numeric (as opposed to narrative) quality criteria, and the realization that the costs of achieving such criteria are more readily measurable than the benefits. The request for proposals goes on to state:

> "However, State agencies charged with developing standards and facilitating their adoption into state regulations, often lack the staff time and funding required to do a

complete analysis of benefits. To assist State lawmakers and the general public in being better informed, State environmental agencies need to be able to accurately characterize the economic value of environmental benefits associated with achieving water quality standards for nutrients. A thorough assessment of these benefits associated with numeric nutrient standards *would apply a production function approach, documenting the direct linkage between excess nitrogen and phosphorus in the water and a loss of ecological goods and services provided to society*, and provide a monetary estimate of benefits from restoring these services" (EPA-OW, 2007, p. 3, emphasis added).

In response to this solicitation we submitted a project that included three main components or modules among its objectives. These include:

i. Development of a eutrophication production function whereby quantitative measures of ambient nutrient levels can be mapped to qualitative indicators of water body quality as reflected by its trophic state.

ii. Development of a revealed and stated preference framework for non-market valuation of the benefits of nutrient reductions that: (a) links to the eutrophication production function; (b) is general in that the software, data sources, and analytical techniques are transferable to any region and scalable for any policy question; and (c) is location-specific in that the parameters of the benefit function can be calibrated based on local conditions and the local policy question of interest.

iii. Transfer of knowledge on how the framework can be applied for regulatory analysis via: (a) a training workshop targeted at state level water quality regulators and analysts; and (b) distribution of software, data sources, and educational materials necessary for implementing the framework.

Our proposal was selected for funding and work began April 2008. In this technical document we summarize work to date on the first of these objectives. In the next section we begin by describing the general goals and strategies for our production function approach. This is followed in Section 3 by a detailed discussion of the data available for fitting our empirical models. Section 4 describes our analytical approach and reports estimation results from the various models we examined. Section 5 provides a summary of the ambient water quality database we have assembled in order to demonstrate the use of our production function approach, and Section 6 provides a summary of illustrative predictions from across our study region. Section 7 concludes the document with a discussion of limitations to our approach, future research opportunities, and a roadmap for the remainder of the project.

2) General Framework

Module 1 of our project focuses on developing a link between measured water quality variables and the qualitative trophic state of a given water body. Eutrophication is a process fueled by nutrients such as nitrogen and phosphorus, and it results in problems that include increased algal growth, reduced water clarity, coloration of surface water, unpleasant odors, and impacts on aquatic life. It is these problems that are perceptible to users and ultimately condition the suitability of lakes for recreation and aesthetic purposes. For this reason we seek a function that relates measured water quality to an index of trophic state, which reflects these perceptible impacts. There is, however, no single variable that is always the best predictor of eutrophication or the water body's trophic state. What is needed is a mapping between several objectively measured variables (such as total nitrogen and phosphorous, chlorophyll, turbidity, etc.) and an index reflecting trophic state and perceptible impacts. To this end we develop a statistical water quality production function relating data on measured water quality and trophic state. To fix ideas, consider the following general specification of a water quality production function:

$$r_k = f(q_{k1},...,q_{kM}), \tag{1}$$

where $q_{k1},\ldots,q_{kM}$ denotes measurements of M different measured water quality variables (e.g. nitrogen, phosphorous, chlorophyll a, etc.) at water body k, $f(\cdot)$ is a function that takes the measured water quality variables as inputs, and r_k is an ordinal ranking (r_k=1,2,...,R) reflecting the qualitative trophic state of the water body. Furthermore define $e_{k1},\ldots,e_{kL}$ as a collection of L perceptible indicators of trophic state such as algal growth, water clarity, water color and smell, and the health of aquatic populations. Finally, suppose that the ordinal rankings are defined such that there is a known, *a priori* given mapping $g(\cdot)$, where:

$$r_k = g(e_{k1},...,e_{kL}). \tag{2}$$

Equations (1) and (2) suggest an operational strategy for estimation of a function that meets our applied needs. First, the relationship illustrated by (2) needs to be defined for the specific application. In the example we examine below for lakes and reservoirs in the inland Southeast, we use a definition for $g(\cdot)$ that is illustrated in Table 1 below. The specifics of this definition are discussed in greater detail in the following section. Second, expert elicitation can be used to relate observations on measured water quality to the rankings 1,...,R. Expert elicitation is a systematic process of interviewing experts to quantify their judgments on the relationships between measured variables and unmeasured outcomes (Meyer and Booker, 2001). In this instance experts first familiarize themselves with the relationship illustrated by equation (2). Then they are presented with experimentally designed data rows corresponding to values of the measured variables $q_1,...,q_M$. For each data row, the expert is asked to judge which ranking (1,...,R) they would assign, based on the given water quality values. Multiple experts provide assessments for multiple data rows that vary in the levels of the measured water quality variables

Table 1: Trophic Status Categories

Category	Water clarity	Color	Algae	Nutrient levels	Oxygen	Odor	Aquatic life
1	Excellent	None	Very little	Very low	Very high	No	Very healthy, abundant
2	Good	Little	Little	Low	High	Little	Healthy, abundant
3	Fair	Some	Moderate	Moderate	Moderate	Little	Somewhat healthy, abundant
4	Poor	Noticeable	High	High	Low	Noticeable	Unhealthy, scarce
5	Poor	Considerable	Very high	Very high	Low to no	Strong offensive	Unhealthy, scarce or none present

presented. In this way, we can obtain a dataset suitable for estimating an empirical version of equation (1). With these two steps the process is completed. For observed values $q_{01},\ldots,q_{0M}$ obtained from a water body indexed by 0 we can predict the trophic state ranking, denoted $\hat{r}_0$, which in turn reflects the perceptible water quality conditions at the water body that matter to people. Hypothesized or actual changes in measured nutrient pollution outcomes can then be used to measure the change in the ranking attributable to the change in measured nutrient levels.

This strategy for estimating a production function clearly requires interviews with experts in the region specific to the policy analysis. In what follows we describe such an exercise for lakes and reservoirs in North Carolina, conducted by project co-PIs Melissa Kenney and Ken Reckhow.

3) Expert Elicitation Data for North Carolina

As part of previous research co-PIs Kenney and Reckhow (see Kenney et al., 2007) undertook a detailed study of eutrophication conditions at nearly 140 lakes and reservoirs in North Carolina. This research included a rigorous expert elicitation component during which 14 experts familiar with NC hydrology considered how seven water quality parameters map into five levels of trophic state. In this section we review this protocol and the resulting data, which will be used for our statistical analysis. We first describe the general approach that was taken,

Table 2: Example Data Row

Photic Total Nitrogen	Photic Total Inorganic Nitrogen	Photic Total Phosphorus	Photic Chlorophyll a	Surface Dissolved Oxygen	Secchi Depth	Photic Turbidity
0.46 mg/l	0.02 mg/l	0.03mg/l	38 μg/l	6.3 mg/l	1.3 m	3.9 NTU

and then provide additional detail on how the elicitation was carried out. The section concludes with a presentation of summary statistics from the data.

Expert Elicitation Approach

Experts were asked to consider how total nitrogen, total inorganic nitrogen, total phosphorous, chlorophyll *a*, Secchi depth measure, dissolved oxygen, and turbidity map into five pre-defined trophic state levels. The categories were defined on an ordinal scale from j=1 to 5, with 1 being the least eutrophic. The five levels were attached to the descriptive criteria arrayed across the columns in Table 1. Each of the 14 experts was presented with 100 rows of data in a form illustrated by Table 2. For each row of data the expert responded to the following question:

- *Imagine 100 different lakes in the* (named NC) *eco-region with the characteristics specified by the given data row. Of the 100 lakes, how many of the lakes would you expect to fall into each of the* (five categories of eutrophication)?

Each expert answered this question for the specific NC eco-region in which they were most familiar. The eco-regions include Coastal (4 experts), Southeastern Plains (1 expert), Piedmont (6 experts), and Blue Ridge (3 experts). The 100 rows of data were designed to reflect realistic combinations of parameter measurements. Indeed, a large majority of the data rows are actual observations taken from North Carolina reservoirs and lakes, while for a small number of rows actual measurements were adjusted to provide greater variability in the most common scenarios. Each expert responded to 50 data rows that were the same across eco-regions ("statewide" rows) and 50 data rows that were specific to the eco-region ("region" rows). Appendix Table A1 shows the 50 data rows that were common across all experts, and Appendix Tables A2-A5 show the rows that are specific to the Piedmont, Coastal, Southeastern Plains, and Blue Ridge eco-regions, respectively.

Expert Elicitation Process

The actual elicitation process unfolded in three steps. Each step was presented separately and all parts were conducted for all the experts who completed the exercise. The first part (approximately two hours) included a discussion about eutrophication processes and designated use impairment, as well as the use of expert judgments in the project. In the second part (approximately one hour training and two to three hours on the expert's own time), the expert provided their judgments on the data rows described above. The elicitor worked through the first few cases with the expert until they felt comfortable working through the remaining cases individually. The third step involved follow up and debriefing. In total, this process took approximately six to eight hours of the expert's time. We briefly describe the main features of these steps. Additional details are found in Kenney et al. (2007) and Kenney (2007).

The first part of the elicitation process occurred during a face-to-face meeting with the expert, at which time the elicitor directed a discussion about eutrophication processes and designated use impairment, as well as the use of expert judgments in this project. A description of the project, why expert assessments were necessary, the protocol for the elicitation, and how the judgments would be used for analysis were provided. An open-ended discussion guided by the following two questions then occurred:

- What are the mechanisms leading to eutrophication (both natural and human-caused)?
- What other variables (non-eutrophication) affect a water body's attainment of designated use?

Table 3: Example of an Expert's Response

parameter	**TN**	**TIN**	**TP**	**Chla**	**DO**	**Secchi**	**Turbidity**
value	0.46	0.02	0.03	38	6.3	1.3	3.9
Ranking	**1**	**2**	**3**	**4**	**5**		
# Lakes	0	10	50	40	0		

This component of the protocol provided perspective on how the expert viewed eutrophication issues, particularly as regards the similarities and differences between eco-regions in North Carolina. Clues as to how different experts might emphasize different measured variables upon making assessments were also gleaned and recorded.

The second step in the process was the most important and involved responding to a workbook of probabilistic questions. Experts viewed the data rows described above and provided answers in the form of probabilistic measures (expressed via the division of 100 hypothetical lakes into the five categories). This allowed the experts to acknowledge both scientific uncertainty and natural variability, and it reflects the realistic notion that the relationship between measured water quality parameters and trophic state is fundamentally stochastic. An example of how a single expert responded to a single row of data is shown in Table 3.

The final step in the protocol involved examining the elicitation data, identifying answers that seemed odd or contradictory, and following up with the expert on these rows. Experts were asked to look at a subset of their data rows and describe why they made a particular assessment. If the experts saw an error in their assessment, they were encouraged to make a correction that more accurately reflects their belief about the trophic state category. This process provided additional perspective on which variables a particular expert thought were important or not important. For straight-forward rows experts tended to rely on three or fewer variables, while for more difficult decisions more of the information was used. Also, experts seemed to ignore dissolved oxygen, since it was measured at the surface rather than via a photic-zone depth

Table 4: Summary of Expert Elicitation Data

	Mean	Std. Error	Median
***Full Data Set* (*N* =1400)**			
Expect Rank	2.97	0.96	3
Mode Rank	2.91	1.08	3
***50 Common Rows* (*N* =700)**			
Expect Rank	2.96	0.90	3.10
Mode Rank	3.01	1.02	3
***50 Common Rows Collapsed* (*N* =50)**			
Expect Rank	2.96	0.69	3.10

integrated sample.

This process provided 1400 rows of explanatory and response variables as shown in Table 3, and these data provide the basis for our analysis. Table 4 provides summaries of the key features of the data. The first set of statistics describes the full dataset, including all 1400 rows. The expected rank is the row-specific weighted average of the five categories, where the weights are given by the experts' responses. The mode rank is the row-specific category that received the highest weight from the expert. The mean and median are approximately three in the dataset, suggesting the typical lake in NC according to these experts would receive a rank of 3. The second set of statistics presents this same information, but limits the calculations to the 50 data rows that were common across the 14 experts (700 total rows). The final set of statistics presents a summary for our collapsed data. Here, the 14 exerts' answers for each of the 50 common rows are first averaged, resulting in a 50 (as opposed to 700) row data set. The summaries presented are over these 50 rows. While the measures of central tendency are similar to the non-collapsed data, the smaller standard error is consistent with the idea that heterogeneity among experts is minimized by first collapsing the data.

4) ANALYSIS

The data gathered via the expert elicitation exercise are our primary source for estimating empirical versions of equation (1). We have investigated several modeling strategies for fitting our production functions. Here we describe our two preferred approaches, which differ primarily in the way we configure the data for analysis. The first, which we refer to as our *ordered logit regression* model, uses disaggregate configurations of the data. The second, which we call our *binomial regression* model, aggregates judgments from the experts before proceeding with the analysis. We describe these two analyses approaches and a number of model estimates in this section.

Ordered Logit Regression

Recall that our basic modeling objective is to relate measured water quality variables to our j=1,...,5 trophic state rankings. These rankings are an example of ordinal data. Ordinal data is characterized by discrete outcomes that have a natural ranking but for which there is no meaningful scale. The best examples are responses to opinion questions that ask people to rate something using scales such as {very poor, poor, average, good, very good}. In this case there is a natural progression from very poor to very good, but the common labeling device of using {1, 2, 3, 4, 5} to denote the categories is devoid of quantitative meaning. Statistical models are needed that predict the probability of particular outcomes while recognizing this progression. A commonly applied approach for statistical modeling of ordinal data is the ordered logit model.

Ordinal outcomes can be modeled as discrete outcomes that occur sequentially as values for an unobserved (or "latent") continuous variable pass specific thresholds. Denote the data generating process for the latent variable for an observation i on decision occasion t by

$$r_{it}^{*} = \beta' q_{it} + u_{it}, \qquad (3)$$

where q_{it} is a vector of covariates (absent an intercept term) thought to influence the ordinal outcome, β is a vector of parameters, and u_{it} is a random variable. In our model, q_{it} is a vector holding row t of measured water quality outcomes examined by expert i. The unobserved latent variable is linked to the observed ordinal outcome by the relationship

$$\begin{aligned} r_{it}^{j} &= 1 \quad \text{if } \alpha_{j-1} < r_{it}^{*} \leq \alpha_{j} \\ r_{it}^{j} &= 0 \quad \text{otherwise,} \end{aligned} \tag{4}$$

where j=1,...,R denotes the R possible ordered outcomes, the α_j's are threshold values, and $\alpha_0=-\infty$ and $\alpha_J=\infty$. From this setup we can state the probability of observing rank j as

$$\begin{aligned} \Pr(j \mid q_{it}) &= \Pr(\alpha_{j-1} < r_{it}^{*} \leq \alpha_{j}) \\ &= \Pr(\alpha_{j-1} < \beta' q_{it} + u_{it} \leq \alpha_{j}). \end{aligned} \tag{5}$$

From this some rearranging makes clear that the probability of observing a particular outcome depends on the probability distribution function for u_i:

$$\begin{aligned} \Pr(j \mid q_{it}) &= \Pr(\alpha_{j-1} - \beta' q_{it} < u_{i} \leq \alpha_{j} - \beta' q_{it}) \\ &= F(\alpha_{j} - \beta' q_{it}) - F(\alpha_{j-1} - \beta' q_{it}), \end{aligned} \tag{6}$$

where $F(\cdot)$ is the cumulative distribution function for u_{it}. Equation (6) makes clear that the probability of an outcome is a function of observed covariates, a known distribution, and the unknown parameters ($\beta,\alpha_2,...,\alpha_{J-1}$), which are estimated via maximum likelihood.

The ordered logit model arises when we assume that u_{it} is logistically distributed such that the cumulative distribution function $F(\cdot)$ is

$$F(z) = \frac{\exp(z)}{1+\exp(z)}. \tag{7}$$

From equations (6) and (7) we can construct the log-likelihood function for a sample of I experts assigning each of T data rows to the R categories as

$$LL(\alpha_1, ...\alpha_{J-1}, \beta) = \sum_{i=1}^{I} \sum_{t=1}^{T} \sum_{j=1}^{R} r_{it}^{j} \times \ln \left[\frac{\exp(\alpha_j - \beta' q_{it})}{1+\exp(\alpha_j - \beta' q_{it})} - \frac{\exp(\alpha_{j-1} - \beta' q_{it})}{1+\exp(\alpha_{j-1} - \beta' q_{it})} \right]. \tag{8}$$

Standard numerical search methods are used to find values of the unknown parameters that maximize (8), which are the maximum likelihood parameter estimates for the ordered logit model.

Once the parameters are estimated, predictions for the probabilities of the different categories conditional on values for q are straightforward to compute using (4) and (5). In particular, the predicted rank for some value of water quality q_0 obtained from a water body indexed 0 is calculated as

$$\hat{r}_0 = \sum_{j=1}^{R} pr(j \mid q_0) \times j. \tag{9}$$

Predicted rankings for specific water bodies can be obtained using equation (9) and actual observations from the water body's quality monitoring stations.

To estimate our ordered logit models, a transformation of the raw data is needed. Recall that our experts provided a *distribution* (i.e. the proportion of lakes that would fall into each category) of ordinal ranks, rather than a single rank, as is needed for this model. To assign a single ordinal rank to each of our 1400 observations (100 from each of 14 experts) we selected the rank that received the highest proportion of the expert's distribution, which is the mode rank as described in Table 4. The average mode rank is 2.91, and the standard error of over one suggests there is usable variability in the data among experts' mode rank responses.

We examined several ordered logit specifications, and we report here sets of results that are useful for predictions in different contexts. Our baseline model includes all 100 answers from each of the 14 experts. This is consistent with the notion that there is a single function that is appropriate for predicting the trophic state in lakes and reservoirs across all four of the North Carolina eco-regions included among our data. Table 5 presents results from three specifications of this model. In all instances the standard errors shown in parenthesis are clustered to reflect the likely correlation among judgments from the same expert.

Table 5: Full Sample Ordered Logit Model Results

VARIABLE	Model 1	Model 2	Model 3
Total Nitrogen	0.436 (0.301)	0.603 (0.269)	1.335 (0.275)
Total Inorganic Nitrogen	0.873 (0.494)	-	-
Total Phosporous	9.792 (2.463)	10.402 (2.606)	11.729 (2.774)
Chlorophyll a	0.076 (0.012)	0.075 (0.011)	0.072 (0.01)
Dissolved Oxygen	-0.004 (0.05)	-	-
Secchi Depth	-0.73 (0.139)	-0.705 (0.137)	-
Turbidity	0.017 (0.009)	0.02 (0.008)	0.035 (0.01)
Cut 2	-1.112 (0.764)	-1.007 (0.593)	0.61 (0.403)
Cut 3	0.535 (0.546)	0.639 (0.396)	2.146 (0.351)
Cut 4	3.044 (0.394)	3.152 (0.404)	4.505 (0.451)
Cut 5	6.264 (0.561)	6.351 (0.483)	7.695 (0.578)
Log-likelihood Value	-1,542.50	-1,544.37	-1,597.41

Model 1 contains all the water quality variables that were presented to the experts. The coefficient estimates are not meaningful in magnitude, but their signs do have a direct interpretation. A positive sign suggests that a higher level of the variable pushes the ranking higher (i.e. towards a worse trophic state), and a negative coefficient means that higher levels of the variable are associated with a better (lower index number) trophic state. Based on this interpretation all of the estimated coefficients have sensible signs. Higher levels of nitrogen, phosphorous, chlorophyll *a*, and turbidity are associated with higher index numbers, and higher levels of positive indicators such as dissolved oxygen and clarity are associated with lower index numbers. In this qualitative sense the model works quite well. As regards statistical performance, with some exceptions, coefficient estimates are generally significant at a 5% level (estimates greater than twice standard the errors). However, both nitrogen types are individually insignificant, as is surface dissolved oxygen. The former likely suggests total nitrogen and total inorganic nitrogen were redundant sources of information for the experts. The latter reflects the fact that surface dissolved oxygen is less relevant than other oxygen measures for predicting trophic state. These observations motivate model 2, which examines coefficient estimates when inorganic nitrogen and dissolved oxygen are excluded. We find that all remaining coefficients are now significant, and a log-likelihood test between models 1 and 2 suggests no loss of statistical fit from the exclusions. Model 3 is motivated by the practical observation that many water bodies in our study region lack measurements for particular variables. For example, in our data for South Carolina reservoirs discussed below, Secchi depth is infrequently observed. In this and similar instances, prediction of the water quality ranking may require use of a model that excludes particular variables. The remaining variables in this model - total nitrogen, total phosphorous, chlorophyll *a*, and turbidity - are perhaps more commonly available. We find all four coefficients are intuitively signed and significant, though a log-likelihood ratio tests suggests a statistically significant loss of explanatory power from their exclusion. The extent to which this has practical implications will be discussed in section 6. Based on analysis of the full sample we conclude that model 2 represents our best specification.

While the individual coefficient magnitudes are not directly interpretable, they can be used to compute *elasticity* measures, which provide unit-free comparisons between the different variables. Specifically, the model estimates can be used to compute the probability for each trophic level, conditional on values for the water quality variables. An elasticity is the percent by which one of these probabilities changes due to a one percent change in a single explanatory variable. Using elasticities we can determine which variables have the largest relative influence on probability predictions. Elasticities from our preferred model (model 2) for each variable and each trophic level are shown in Table 6. For lower index levels (better quality) the pollution measures have negative signs, since higher pollution decreases the probability of a good index; the opposite holds for the higher index number (worse quality). In all instances we find that

Table 6: Elasticity Measures

VARIABLE	Category 1	Category 2	Category 3	Category 4	Category 5
Total Nitrogen	-0.289	-0.224	-0.004	0.231	0.301
Total Phosporous	-0.556	-0.430	-0.008	0.444	0.578
Chlorophyll a	-1.755	-1.358	-0.024	1.404	1.826
Secchi Depth	0.908	0.703	0.013	-0.727	-0.945
Turbidity	-0.145	-0.112	-0.002	0.116	0.151

chlorophyll *a* has largest elasticity, suggesting this was on average the most important variable driving experts' judgments. Secchi depth was also relatively important, followed by total phosphorous and total nitrogen.

The full models presented in Table 5 pool expert judgments from across the state, resulting in a single parameterization for use in subsequent predictions, regardless of the eco-region in which a lake sits. Given the differing physical characteristics of lakes and reservoirs in different eco-regions, however, it may in some instances be desirable to use a model specific to an eco-region type. Because the experts were asked to make their judgments conditional on a specific eco-region, it is possible to use subsets of the data to estimate region-specific or lumped-region models. This comes, of course, at a cost of fewer observations used for estimation. Table 7 presents results for three disaggregate models as well as the state-wide model repeated from Table 5, each using the preferred specification. We have combined observations from the Piedmont and Southeastern Plains experts, since only one expert from the latter region participated. The Blue Ridge and Coastal models include only experts from their respective regions. We find some differences in coefficient estimates, the most notable being the size differences in the nitrogen and phosphorus coefficients between the Blue Ridge and Piedmont models. Elasticity estimates that we examined suggested that, while chlorophyll *a* and Secchi depth remain the most important predictors in the Blue Ridge as elsewhere, total nitrogen and total phosphorous are comparatively more important predictors of trophic state in this region

Table 7: Region-Specific Ordered Logit Results

VARIABLE	Statewide	Piedmont/SE Plains	Blue Ridge	Coastal
Total Nitrogen	0.603 (0.26)	0.907 (0.18)	1.381 (0.688)	-0.169 (0.468)
Total Phosporous	10.402 (2.606)	7.192 (2.252)	16.289 (3.639)	14.322 (8.631)
Chlorophyll a	0.075 (0.011)	0.081 (0.016)	0.077 (0.015)	0.124 (0.014)
Secchi Depth	-0.705 (0.137)	-0.819 (0.22)	-0.937 (0.353)	-0.561 (0.142)
Turbidity	0.02 (0.008)	0.036 (0.004)	0.035 (0.03)	0.039 (0.008)
Cut 2	-1.007 (0.593)	-1.519 (0.99)	-2.093 (0.448)	1.622 (0.857)
Cut 3	0.639 (0.396)	0.426 (0.597)	0.053 (0.17)	2.964 (0.298)
Cut 4	3.152 (0.404)	3.196 (0.558)	3.301 (0.676)	5.386 (0.15)
Cut 5	6.351 (0.483)	6.413 (0.606)	7.329 (0.454)	8.807 (1.012)

than elsewhere in the state.

Binomial Regression

Our second analysis approach mirrors the models presented by Kenney (2008), and begins with some aggregation of the data to average out heterogeneity among the experts. Consider for example the t=1,...50 rows of data that were common for all 14 experts, and let w_{ijt} denote the proportion expert i assigned to category j for data row t. Define the average proportion assigned by the 14 experts as

$$w_{jt} = \frac{1}{14}\sum_{i=1}^{14} w_{ijt}, \quad j = 1, \ldots, 5, \tag{10}$$

and note that the w_{jt}'s can be interpreted as the derived consensus among the panel of experts as to how row t of quality measurements maps to a distribution for the five trophic state levels. With this we can define the expected rank for data row t as

$$E(r_t) = \sum_{j=1}^{5} j \times w_{jt}. \tag{11}$$

This is the statistic that was summarized in the last row of Table 4. For estimation it is convenient to normalize $E(r_t)$ such that

$$z_t = \frac{E(r_t)}{5} = \frac{1}{5}\sum_{j=1}^{5} j \times w_{jt}, \tag{12}$$

where z_t is contained in the unit interval. Equation (12) completes the data manipulation needed for estimation. The estimating equation then is a simple linear regression

$$\ln\left(\frac{z_t}{1-z_t}\right) = \theta' q_t + \varepsilon_t, \tag{13}$$

where q_t is the vector of water quality measures contained in row t. Equation (13) is estimated by least squares and estimates for the coefficient vector θ are obtained. The form of (13) suggests prediction of z for any value of water quality measurements q_0 is given by

$$\hat{z}_0 = \frac{\exp(\theta' q_0)}{1+\exp(\theta' q_0)}. \tag{14}$$

With the prediction for z, we can compute the implied probability of rank j conditional on water quality values q_0 using the binomial distribution as

$$p(j \mid q_0) = \frac{5!}{j!(5-j)!} \times \hat{z}_0^{\,j} \times (1-\hat{z}_0)^{5-j}, \tag{15}$$

and equation (9) can be used to compute the predicted trophic state.

We estimate five versions of equation (13). The first is a state-wide model that uses the 50 data rows common to the 14 experts. We then estimate region-specific models, which use the 100 rows of data that were common for the experts within the specific region. As described above, the experts' answers for common data rows were first averaged, and then the regression was estimated.

Table 8 presents results of estimation for our state-wide binomial regression models. These models are based on the average among the 14 experts over the 50 common data rows. Models 1 and 2 here are comparable to the corresponding ordered logit specifications presented in Table 5, and quite similar conclusions emerge from the estimates. The coefficient estimates

Table 8: Statewide Binomial Regression Results

VARIABLE	Model 1	Model 2	Model 3
Total Nitrogen	0.142 (0.086)	0.139 (0.083)	0.422 (0.112)
Total Inorganic Nitrogen	0.295 (0.212)	-	-0.038 (0.302)
Total Phosporous	4.256 (0.496)	4.193 (0.47)	5.346 (0.691)
Chlorophyll a	0.027 (0.002)	0.028 (0.001)	0.025 (0.002)
Dissolved Oxygen	0.025 (0.016)	-	0.051 (0.023)
Secchi Depth	-0.201 (0.028)	-0.202 (0.028)	-
Turbidity	0.009 (0.003)	0.011 (0.003)	0.013 (0.004)
Constant	-0.642 (0.159)	-0.444 (0.079)	-1.275 (0.192)

Table 9: Region-Specific Binomial Regression Results

VARIABLE	Piedmont/SE Plains	Blue Ridge	Coastal
Total Nitrogen	0.142 (0.086)	0.447 (0.115)	-0.109 (0.115)
Total Inorganic Nitrogen	0.295 (0.212)	0.065 (0.196)	1.145 (0.284)
Total Phosporous	4.256 (0.496)	4.844 (0.708)	4.634 (0.667)
Chlorophyll a	0.027 (0.002)	0.02 (0.002)	0.04 (0.002)
Dissolved Oxygen	0.025 (0.016)	-0.211 (0.027)	-0.181 (0.038)
Secchi Depth	-0.201 (0.028)	0.022 (0.015)	0.027 (0.022)
Turbidity	0.009 (0.003)	0.007 (0.004)	0.006 (0.004)
Constant	-0.642 (0.159)	-0.402 (0.169)	-1.281 (0.216)

are sensibly signed and generally significant at the 5% level, though as with the ordered logit model the two nitrogen variables seem redundant, and the dissolved oxygen variable provides little explanatory power. As with the ordered logit model a positive coefficient implies higher levels of the variable push the trophic state ranking higher (generally worse water quality), while the opposite holds for negative coefficients. Model 3 is included for use in our predictive exercises, where observations on Secchi depth are often missing. The region specific models shown in Table 9 also provide similar results as their ordered logit counterparts. We find that total nitrogen levels are more important in predicting trophic state for the Blue Ridge region than for others in the state.

Taken together the results from our two modeling approaches suggest a qualitative robustness in how we quantify the role of the different water quality measures in predicting trophic state. We consistently find that chlorophyll *a* and Secchi depth are the most important factors in predicting quality outcomes, with total nitrogen and total phosphorus also playing a notable role. In Section 6 we examine the extent to which similar predictions from the models arise. In the next section we discuss the data needed to carry out predictions across our study region.

5) WATER QUALITY DATA

Our objective is to use the models discussed above to predict the trophic state of water bodies throughout our study region. A necessary condition for this is the availability of ambient water quality measurements from the lakes and reservoirs of interest. Potential sources of quality measurements include federal, state, local, and private monitoring networks. The availability, completeness, and reliability of monitoring network data varies widely within and across states. As we discuss in greater detail below, the absence of sufficient water quality measurements is likely to be the main impediment to our ongoing efforts to make our approach operational. In this section we describe efforts to obtain water quality information for two states in our study region, which we use to demonstrate our methodology. We focus on and summarize information for North Carolina and South Carolina. In Section 6 this information is then used to provide a series of illustrative predictions of trophic state for lakes and reservoirs in the two states.

Water quality monitoring is primarily carried out by state and local agencies, and these agencies are responsible for the design and maintenance of the monitoring station network and resulting data. To provide a single repository for data generated by the myriad of agencies, EPA maintains the STORET system. This is a database of measurements deposited by government and private managers, and it is the primary vehicle through which information on water quality across multiple regions and agencies can be obtained. Online queries allow users to download information for specific locations, hydrological units, or monitoring stations. Filters for water quality parameters of interest (e.g. phosphorous, dissolved oxygen) can be used, and the information arrives in spreadsheet readable form. Our intent was to rely primarily on the STORET system to obtain the water quality information needed for the demonstrations in this report, and for subsequent project-related analysis. A potential problem with this strategy is that the STORET system may not include all potentially useful information for a given region or water body. There is variability across agencies in the timing of data uploads, and some monitoring station information (particularly for non-government networks and ad hoc monitoring activities) may not be deposited. Thus any sparseness of data availability may be due to incomplete assembly of relevant information or an actual lack of information. The former is less worrying, because state managers who use this protocol will likely have better institutional knowledge of local data sources than we do. The latter is more of an issue, and we return to this point below.

To gather water quality measurements for lakes and reservoirs in our study region we began with a consistent STORET download protocol for each state. Searching by geographic region, the following fields were coded:

- **State** - *state name* (North Carolina, South Carolina)
- **Station Type** - *lake* and *reservoir*
- **Date** - *January 1, 2005 - April 10, 2009*
- **Activity Medium** - *water*
- **Activity Intent** - *select all*

- **Characteristic -** *Secchi Disk Depth; Chlorophyll a* (various measures)*; Phosphorus as P; Nitrogen, Kjeldahl; Nitrogen, Nitrite (NO2) + Nitrate (NO3) as N; Nitrogen, ammonia as N* or *Nitrogen, ammonia as NH3; Turbidity; Dissolved oxygen*.

For North Carolina this protocol resulted in 4,119 data points among the eight characteristics included. For South Carolina 20,049 measurements were obtained. We discuss STORET and available auxiliary data, and subsequent formatting for each state in turn.

The downloaded data from North Carolina are based on samples taken from only fourteen unique stations that provided data for the years 2005-2007. Only a small fraction of lakes and reservoirs in the state are represented. Conspicuously absent are major water bodies such as Jordan Lake, Falls Lake, and Kerr Lake, among others. While monitoring stations associated with these lakes can be found via STORET text string searches, queries on these stations did not produce any actual data. Review of materials published by the NC Division of Water Quality suggests monitoring of, for example, Falls and Jordan Lakes has occurred in recent years, though the information is not obviously available for download. Given the paucity of information from STORET we have elected to use data from other sources for our North Carolina demonstrations. As part of the expert elicitation project co-PIs Kenney and Reckhow assembled a near census of lake and reservoir water quality measurements for North Carolina. This was obtained by direct contacts with NC Division of Water Quality personnel, and it seems to represent information that is not uploaded to STORET. Using the Kenney/Reckhow data for our NC demonstration we focus on a selection of lakes and reservoirs spread throughout the state. These water bodies are listed in Table 10, along with the number of complete observations available for each. A complete observation for a NC lake consists of observations for the seven relevant water quality parameters at a particular date/time and at the same location. The

Table 10: Demonstration Lakes and Data Summaries

North Carolina	Obs.	TN (mg/l)	TIN (mg/l)	TP (mg/l)	Chla (μg/l)	DO (mb/l)	Secchi (m)	Turbidity (NTU)
Belews Lake	15	0.11	0.02	0.02	2	6.6	3.2	2.20
High Rock Lake	34	0.895	0.245	0.065	37.5	9.05	0.6	12.50
Jordan Lake	22	0.82	0.04	0.075	33	7.9	0.6	12.0
Kerr Scott Reservoir	15	0.17	0.03	0.02	7	8.5	2.2	3.60
Lake Norman	24	0.12	0.02	0.02	4	7.9	2.3	2.30
Limestone Lake	13	1.57	0.15	0.18	23	5.1	0.3	12.00
Old Town Reservoir	12	0.395	0.02	0.015	5	7.75	1.95	2.45
South Carolina								
Lake Greenwood	37	0.63	0.37	0.03	9.01	9.52	-	7.05
Lake Hartwell	69	0.47	0.31	0.05	4.11	8.40	-	2.50
Lake Keowee	37	0.59	0.25	0.04	1.43	8.39	-	1.25
Lake Marion	151	0.67	0.49	0.06	6.30	8.10	0.94	5.45
Lake Moultrie	49	0.58	0.37	0.03	6.10	9.20	1.37	2.75
Lake Murray	60	0.51	0.26	0.04	8.51	8.63	-	3.53
Lake Wateree	32	0.73	0.50	0.04	10.40	8.65	-	4.55
Lake Wylie	35	0.57	0.42	0.03	5.60	9.26	-	4.05

observations are literal measurements in that no averaging or other combining was undertaken. A summary of the median water quality parameter values for each of the seven variables entering our models is also shown in Table 10.

The measurements from the South Carolina STORET query are nominally more complete. Over 20,000 records were obtained for the years 2005-2009. For our demonstration we focus on data for the eight lakes that are listed in Table 10. Data records were assigned to the eight lakes based on manually matching station names. The matching process produced over 11,000 data points for the nutrient measures of interest for our analysis (the majority from Lake Marion). Even here, however, there are data thinness challenges. Most of the lakes are regularly (i.e. monthly or bi-monthly) measured for dissolved oxygen, phosphorus, turbidity, and the various nitrogen types. Often absent, however, are regular measurements for Secchi disk and chlorophyll *a* - the parameters our analyses suggests have the greatest importance for predicting trophic state. Furthermore the different parameters are typically not measured simultaneously at the same monitoring station. Because of this we have collapsed the data into lake/sample date groupings for summary purposes. Specifically, for each water quality variable of interest we have selected all data points available for a particular lake on a given date. We then assign the median among the measurements as the measure of interest. Thus a characterization of a lake's water quality on a given day is potentially obtained from multiple stations and measurements. A complete observation for a SC lake includes measures of all seven variables obtained this way. While we have undertaken this aggregation largely out of pragmatism, it may have other virtues for our purposes. Via this collapsing strategy we have assembled 470 data rows for the eight SC lakes, but very few are complete and may not be useable for prediction exercises. Table 10 provides a summary of the medians over these data rows for the lakes of interest.

6) ILLUSTRATIVE PREDICTIONS

In this section we examine predictions for trophic state at the focus lakes listed in Table 10, using the model estimates presented in Section 4 and the data summarized in Section 5. We present estimates at baseline (current) conditions, and then discuss predictions for counterfactual situations involving improvements (defined by hypothetical levels of the variables that would reduce eutrophication) in water quality measurements.

With both the ordered logit and binomial regression models there are two approaches we can take for computing predicted trophic state. The first simply uses the median of the all the observed water quality parameters available for a particular lake, and with these computes a single prediction. This approach would, for example, directly use the values presented in Table 10 to compute baseline predictions for the NC and SC focus lakes. This strategy is computationally straight-forward, and eliminates much of the noise in the water quality measurements ex ante. We refer to this as the *median* strategy. The second strategy computes trophic state predictions for the individually observed quality measurements, thereby producing a distribution of predictions for a particular lake. This approach would, for example, use the 15 observations available for North Carolina's Bellows Lake to produce 15 predictions for its trophic state. Summaries (i.e. mean, median, spread) over the distribution of predictions can then be used to characterize the water quality at the water body. The advantages of this approach are that it provides a better sense of the precision with which we can characterize a lake, and it better reflects natural variability. However, these advantages can only be realized when data is reasonably complete and representative of the median and range of conditions. We refer to this as the *distribution* strategy. In what follows we examine both approaches. In all instances the actual predictions are carried out using the methods discussed in Section 4. We rely on our state-wide models to provide the cleanest comparison across and within the different approaches.

Tables 11 and 12 contain our predictions, where the former focuses on the median strategy and the latter on the distribution strategy. Except where noted the ordered logit predictions come from the state-wide model with our preferred specification (model 2 in Table 5), and the binomial predictions are from the state-wide, complete model shown in Table 8. The exceptions are for lakes in South Carolina for which no measurements on Secchi depth are available (all lakes aside from Lakes Marion and Moultrie). In these instances we have used model 3 in Table 5 for the ordered logit predictions, and model 3 in Table 9 for the binomial regression, which includes all parameters aside from Secchi depth. The predictions for the distribution strategy include point estimates and the inter-quartile range, which is the distance between the 25th and 75 percentiles of the empirical distribution of predictions. Because the South Carolina lakes outside of Lakes Marion and Moultrie lacked any substantial chlorophyll *a*

Table 11: Trophic State Predictions - Median Strategy

	Baseline Predictions		**20% Improvement**		**Eutromod Predictions**	
North Carolina	*Logit*	*Binomial*	*Logit*	*Binomial*	*Logit*	*Binomial*
Belews Lake	1.40	1.60	1.26	1.51	1.70	1.78
High Rock Lake	3.70	3.72	3.36	3.41	2.46	2.60
Jordan Lake	3.60	3.54	3.27	3.24	2.48	2.53
Kerr Scott Reservoir	1.83	1.95	1.63	1.84	1.74	1.91
Lake Norman	1.68	1.82	1.51	1.73	1.70	1.85
Limestone Lake	3.93	3.83	3.60	3.50	3.09	3.04
Old Town Reservoir	1.87	1.93	1.68	1.84	1.73	1.93
South Carolina						
Lake Greenwood	2.38	2.46	2.21	2.41	2.04	2.25
Lake Hartwell	2.13	2.22	1.99	2.19	2.09	2.14
Lake Keowee	2.04	2.14	1.92	2.12	2.05	2.14
Lake Marion	2.53	2.61	2.34	2.45	2.25	2.28
Lake Moultrie	2.21	2.32	2.02	2.20	1.98	2.15
Lake Murray	2.29	2.35	2.12	2.30	2.07	2.16
Lake Wateree	2.52	2.53	2.31	2.44	2.16	2.27
Lake Wylie	2.15	2.25	2.01	2.23	1.95	2.14

Table 12: Trophic State Predictions - Distribution Strategy

	Baseline Median (quartile range)	
North Carolina	*logit*	*Binomial*
Belews Lake	1.41 (0.09)	1.61 (0.06)
High Rock Lake	3.71 (0.65)	3.72 (0.72)
Jordan Lake	3.73 (0.72)	3.68 (0.77)
Kerr Scott Reservoir	1.83 (0.37)	1.94 (0.29)
Lake Norman	1.67 (0.35)	1.82 (0.23)
Limestone Lake	4.08 (1.47)	3.97 (1.38)
Old Town Reservoir	1.9 (0.3)	1.95 (0.24)
South Carolina		
Lake Marion	2.5 (0.36)	2.57 (0.28)
Lake Moultrie	2.34 (0.41)	2.44 (0.36)

measurements, we only examine estimates from the distribution approach for these two lakes.

Consider first the baseline predictions that are contained in the first two columns of results in both tables. For both the ordered logit and binomial regression models the point estimates from the two approaches are virtually identical. This suggests the value added from the predictions using the distribution method lies in summarizing the inherent uncertainty in how the collection of water quality measurements taken at different points in time and space map into a single water quality index. The extent to which this provides a good measure of uncertainty depends, of course, on having sufficient observations to characterize the range of water quality parameter values a lake might take. For many of our focus lakes - particularly in South Carolina - the number of available data points is likely too small to provide much resolution on this statistic. For this reason we focus primarily on the results generated from the median strategy. A comparison between baseline estimates from the ordered logit and binomial regression predictions suggest qualitatively similar outcomes, though there are some quantitative differences. It seems that when there is a comparatively large difference between the two, the binomial model predicts a higher (worse quality) index.

Our model is also designed for use in predicting the extent to which decreases in nutrient pollution will lead to qualitative improvements in trophic state. As a demonstration of this capability of the model we examine two types of counterfactual scenarios. The first is purely illustrative and examines how our predictions change when all quality measures improve by 20% (i.e. total nitrogen, total phosphorous, chlorophyll *a*, and turbidity decrease, and Secchi depth and dissolved oxygen increase). The second and third columns of Table 11 provide predictions for the lakes' trophic state under these changed conditions. For the ordered logit model the change in the predicted trophic state for the lakes ranges from 8-11% of the initial prediction among the NC lakes, and 6-9% for the SC lakes. The size of the predicted change is comparatively smaller for the binomial model. Here we find changes that range from 4-8% for the NC lakes, and 1-6% for the SC lakes. These examples suggest there is perhaps more potential for movement along the range of trophic state predictions with the ordered logit model relative to the binomial model. This, however, would need to be confirmed with a larger sample of lakes.

Our final analysis is designed to provide a more realistic demonstration of the models' counterfactual prediction capabilities. The seven water quality parameters that enter our model are correlated, and changes in nutrient source loadings will lead to a (partially) predictable but non-uniform change in the parameters' values away from baseline. Existing models provide quantifications of these relationships, and we describe the well-known *Eutromod* model for Southeastern lakes based on Reckhow (1988) and Reckhow et al. (1993) here. Our objective is to observe the baseline measurements of parameters at a water body, postulate a reduction in nutrient loadings into the water body, and compute the predicted change in parameter values. The latter will then be used to predict the change in trophic state resulting from the nutrient loadings reduction.

We focus on predicting changes in four variables: total nitrogen, total phosphorus, Secchi depth, and chlorophyll *a*. To this end define the concentration of total nitrogen and total phosphorus from the watershed inflow waters to the lake of interest by TP_f and TN_f, respectively. In Eutromod in-lake concentration predictions TP^1 and TN^1 are based on mechanistic descriptions given by

$$\begin{aligned} \log 10(TP^1) &= \log 10\left[TP_f \;/\; (1+g_{TP}t)\right] \\ \log 10(TN^1) &= \log 10\left[TN_f \;/\; (1+g_{TN}t)\right], \end{aligned} \tag{16}$$

where t is the hydraulic detention time, and g_{TN} and g_{TP} are the trapping parameters for nitrogen and phosphorus, respectively. Reckhow (1988) estimates equations for the trapping parameters in the Southeastern region as

$$\begin{aligned} g_{TP} &= 3.0(TP_f)^{0.53} t^{-0.75} d^{0.58} \\ g_{TN} &= 0.76 t^{-0.75}, \end{aligned} \tag{17}$$

where d is the mean depth. Based on the predicted values for TP^1 and TN^1, Reckhow et al. (1993) and Reckhow (1988) present predictive equations for chlorophyll *a* and Secchi depth, respectively, as

$$\begin{aligned} \log 10(Chla^1) &= 2.33\left[\log 10(TP^1)\right]^{0.775} \times \left[\log 10(TN^1)\right]^{0.317} \\ \log 10(Secchi^1) &= -0.47\left[\log 10(TP^1)\right]^{-0.364} \times \log 10(t^{0.102}) \times \log 10(d^{0.137}), \end{aligned} \tag{18}$$

where $Chla^1$ and $Secchi^1$ are the respective predictions. With observation of TN_f and TP_f, equations (16) - (18) can be used to predict either the baseline or counterfactual values of the four water quality measures.

In instances where TP_f and TN_f are not observed, for the baseline conditions the nutrient inflow can be approximated using retention coefficients. In particular,

$$\begin{aligned} TP_f &= TP / (1 - R_P) \\ TN_f &= TN / (1 - R_N), \end{aligned} \tag{19}$$

where R_P and R_N are the retention coefficients for nitrogen and phosphorus, respectively.

For our application we consider a hypothetical decrease in nutrient loadings that leads to a 30% reduction in lake in-flow concentrations of total nitrogen and total phosphorus. Based on this we predict new levels of ambient total nitrogen, total phosphorus, chlorophyll *a*, and Secchi depth in the lake, which are then used to predict the new trophic state. To make this operational we need to set values for lake depth, detention time, and phosphorus and nitrogen retention. We follow Reckhow (1988) and set values tailored to the Southeast based on the USEPA National Eutrophication Survey. We use the retention levels and observed total nitrogen and total phosphorus to set baseline concentration inflows, and scale this by 0.70 to simulate the improvement. We assume the values for turbidity, inorganic nitrogen, and dissolved oxygen remain constant in the counterfactual scenario, since models have not been developed that allow us to predict their changes.

Predictions for our North Carolina and South Carolina focus lakes are shown in the last two columns of Table 11. In a few instances the predictions for the improved trophic state are actually *worse* than the baseline. This is due to imperfect predictions from eutromod, which is most apparent when the baseline condition is relatively non-eutrophic. In these cases the improved predictions for chlorophyll *a* and Secchi depth tend to be worse than their baseline, leading to the counter intuitive result. Focusing on the predictions that show an actual improvement, the logit model has a median percentage improvement in the trophic ranking of around 11%, while the binomial model produces a median improvement among all the lakes of 9%. There is variability in the size of improvement among the different lakes, however. Perhaps not surprisingly, the lakes with a higher trophic state at baseline (i.e. the more eutrophic lakes) have a better percentage improvement than those that are less eutrophic at baseline. For example, for North Carolina's High Rock Lake we predict a 30-33% improvement in trophic ranking resulting from the 30% decrease input loading. This contrasts with the 2-4% rank improvement for South Carolina's Lake Hartwell, which has a baseline ranking of 2.13 on our scale. From this exercise we conclude that the more eutrophic lakes will improve their rankings to a greater extent from reduced nutrient loading than their less eutrophic counterparts, perhaps because the cleaner lakes have less distance to move. We see this as additional evidence that our model predictions are working as expected.

7) Discussion and Conclusion

Our objective in writing this report has been to report on the first year of our project team's efforts to provide a water quality production function that is capable of predicting qualitative nutrient pollution rankings at lakes and reservoirs as a function of measured water quality. We have relied on an expert elicitation protocol to obtain data relating measured water quality parameters to qualitative rankings of a water body's trophic state. Two different modeling approaches applied to our data provide similar characterizations of how water quality parameters such as total nitrogen, total phosphorus, chlorophyll *a*, Secchi depth, dissolved oxygen, and turbidity map to nutrient-pollution quality rankings. Our sense is that this aspect of the project has been quite successful. Our mapping provides a robust means by which observations on a lake's objectively measured quality can be used to construct a prediction of the lake's subjective or qualitative nutrient pollution index. Ultimately, however, the reliability of predictions depends on the availability of sufficient monitoring network measurements from the water body. In our demonstrations using lakes and reservoirs in North Carolina and South Carolina we have shown the range of capabilities of our models and their limitations. Our illustrative predictions for North Carolina, where we had access to a wider range of quality data, are arguably more reliable than those for South Carolina, where we were constrained by limited observations for Secchi depth and chlorophyll *a*. Because these two parameters are the strongest predictors of trophic state, our ability to characterize lakes that lack these measurements will be much more limited. Nonetheless constrained versions of our models that eliminate missing quality variables may be useful, in some instances, for providing rough predictions when certain quality measurements are limited or absent.

To conclude the report we discuss additional limitations and uncertainties inherent in using our model for predictive exercises and describe the next steps in our research. Perhaps most importantly, the expert elicitation data we have used focused on North Carolina, and the experts were asked to consider rankings in the specific context of the eco-region in which they were most expert. Because of this, there are limits to how far our production function can be geographically moved away from North Carolina and still produce meaningful predictions. Our sense is that the inland Southeast Piedmont regions and reservoirs are suitable for transferring our function, but that the coastal and mountainous regions (and natural lake areas) are less so. We have relied on our state-wide models for our prediction demonstrations because previous work (see Kenney, 200x) has suggested these models perform better. It may be, however, that the Blue Ridge regional model would be better for analysis of lakes and reservoirs in higher elevation areas, while the state-wide model is preferred for all else. In all cases we have little confidence in the models' ability to predict outcomes for natural lakes and coastal areas. We stress that these statements are hard to evaluate quantitatively because out of sample predictions cannot be examined for accuracy. Thus, applications of our models beyond similar reservoir systems and the associated hydrogeomorphology that one might find in South Carolina and Virginia requires additional judgment, and the usefulness of predictions will depend on the specific needs of the application.

Judgments on the use of sparse monitoring station data will also be necessary, and the usefulness of predictions from areas with little available data will also depend on the specific needs of the application. For our South Carolina example we have pooled measurements taken from multiple stations on the same day to produce 'observations' for use in our predictions. Further data aggregation, such as pooling all measurements from all stations in a given month for a lake, might also be sensible in some instances. In all cases prediction results should be reported with discussion of how the input data was obtained and formatted, and it should be explicitly noted that pooled measure will reflect central tendencies rather than possible (and possibly interesting) extreme outcomes. Finally, care must be taken to recognize that water quality parameters can be differently measured - both in terms of the depth of sample and laboratory procedures used. If measurement methods are substantially different than those explained during the expert elicitation process, the results may be inaccurate.

While acknowledging these limitations, our sense is that the water quality modeling work we've done is suitably rigorous, transparent, and reliable enough to begin merging predictions into our economic models for valuation purposes. To this end, we will begin working on a more complete suite of predictions for the various water bodies we are likely to consider as part of our economic analysis. This will proceed simultaneously with the continued development of our economic modeling approach.

8) REFERENCES

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Appendix

Table A1: Common Data Rows

Photic Total Nitrogen mg/L	Photic Total Inorganic Nitrogen mg/L	Photic Total Phosphorus mg/L	Photic Chlorophyll a µg/L	Surface Dissolved Oxygen mg/L	Secchi Depth meters	Photic Turbidity NTU
0.46	0.02	0.03	38	6.3	1.3	3.9
0.40	0.01	0.01	16	8.2	0.9	10.0
0.79	0.24	0.03	26	7.6	0.8	7.2
0.41	0.02	0.04	40	11.8	1.4	3.3
0.61	0.19	0.04	34	10.3	1.5	2.8
0.21	0.06	0.04	1	6.0	1.9	6.8
0.63	0.02	0.05	24	8.9	0.4	11.0
0.46	0.09	0.06	7	6.2	1.1	15.0
1.06	0.72	0.19	4	6.9	0.6	60.0
0.21	0.05	0.01	1	7.7	3.0	0.4
0.39	0.14	0.02	9	7.9	1.1	1.1
0.61	0.06	0.18	11	8.5	0.5	6.6
0.21	0.01	0.02	38	7.6	0.8	4.7
0.57	0.02	0.04	51	9.0	1.2	11.0
0.39	0.02	0.02	25	7.5	1.0	2.1
0.41	0.07	0.03	10	8.2	2.1	2.1
0.41	0.02	0.08	24	9.4	0.5	18.0
0.45	0.03	0.05	16	7.2	0.4	18.0
0.31	0.06	0.02	36	7.7	2.4	5.2
1.41	0.03	0.01	23	8.7	0.3	23.0
0.21	0.08	0.03	40	7.7	2.2	5.4
0.25	0.01	0.02	50	14.1	0.7	10.0
0.91	0.05	0.15	31	5.8	0.4	7.8
0.33	0.05	0.01	16	8.5	2.9	2.0
0.71	0.02	0.08	34	7.8	0.5	6.2
0.31	0.05	0.01	36	8.0	3.5	1.0
0.32	0.06	0.05	25	9.4	1.4	2.5
0.06	0.04	0.03	1	7.5	1.3	1.7
0.11	0.02	0.02	32	8.0	3.0	1.1
0.53	0.06	0.11	30	8.9	0.5	8.0
0.41	0.04	0.03	39	8.3	0.4	8.3
0.21	0.04	0.05	3	7.2	1.9	2.2
0.31	0.06	0.02	38	8.2	1.7	9.8
0.21	0.02	0.01	10	9.0	2.3	3.0
0.30	0.01	0.03	46	9.3	0.6	16.0
0.31	0.04	0.07	20	7.2	1.8	15.0
0.61	0.02	0.04	57	7.5	1.9	7.2
0.40	0.11	0.04	44	8.3	1.2	7.8
0.51	0.02	0.11	42	8.2	0.5	9.3
1.42	0.15	0.18	30	4.4	0.3	11.0
0.86	0.18	0.25	29	7.0	0.5	5.2
0.69	0.20	0.03	1	6.1	0.5	5.2
1.22	0.56	0.07	40	7.9	0.3	7.5
0.51	0.03	0.02	40	10.0	0.8	4.7
0.33	0.07	0.03	32	10.5	1.6	5.0
0.21	0.01	0.05	26	8.3	2.6	4.7
0.21	0.10	0.02	56	8.0	4.8	3.8
1.71	0.03	0.02	26	8.7	0.3	25.0
0.37	0.02	0.02	20	8.0	0.8	10.0
0.11	0.02	0.02	1	7.3	1.9	1.7

Table A2: Piedmont-Specific Data Rows

Photic Total Nitrogen mg/L	Photic Total Inorganic Nitrogen mg/L	Photic Total Phosphorus mg/L	Photic Chlorophyll a µg/L	Surface Dissolved Oxygen mg/L	Secchi Depth meters	Photic Turbidity NTU
0.47	0.02	0.02	12	8.1	2.3	3.7
0.28	0.01	0.04	10	7.8	1.0	4.2
0.41	0.03	0.01	18	9.0	3.4	6.2
0.55	0.02	0.04	16	9.4	2.0	2.2
0.24	0.09	0.02	18	8.3	1.7	12.0
1.14	0.57	0.18	44	9.3	0.3	12.0
0.91	0.51	0.18	28	7.7	0.6	9.2
0.11	0.04	0.01	7	7.8	1.8	2.3
0.61	0.04	0.01	7	8.6	0.8	2.1
0.11	0.02	0.02	9	7.5	2.1	3.2
0.62	0.02	0.05	36	8.0	1.1	9.7
0.21	0.03	0.02	6	6.9	3.2	4.2
0.31	0.02	0.02	5	7.2	2.4	2.6
0.42	0.05	0.04	27	7.7	2.0	3.2
0.21	0.01	0.03	3	8.0	2.5	1.0
0.42	0.09	0.03	16	4.9	1.0	2.0
0.67	0.03	0.05	40	8.4	0.8	5.4
0.71	0.02	0.08	34	7.8	0.5	6.2
0.81	0.04	0.05	95	11.8	0.6	14.0
0.41	0.03	0.05	68	7.7	1.5	3.3
0.31	0.03	0.03	5	7.7	1.6	2.0
0.41	0.06	0.03	7	8.2	1.9	1.6
0.48	0.02	0.03	11	8.4	1.6	3.2
0.13	0.05	0.01	9	8.4	2.7	3.1
0.40	0.01	0.01	5	8.0	2.2	4.3
0.63	0.02	0.09	27	8.3	1.2	7.0
0.53	0.01	0.03	19	8.3	1.9	1.6
1.03	0.35	0.21	33	8.4	0.5	11.0
0.71	0.17	0.12	34	7.2	0.7	3.3
1.01	0.10	0.09	39	9.0	0.3	9.2
0.63	0.10	0.03	23	5.5	1.9	2.1
0.86	0.09	0.14	39	9.2	0.3	18.0
0.21	0.03	0.01	3	7.8	2.0	1.6
1.90	1.23	0.26	39	12.0	0.3	7.9
0.41	0.05	0.03	27	8.5	3.0	1.8
1.11	0.09	0.31	17	11.9	0.4	25.0
0.51	0.15	0.05	51	9.6	0.6	7.6
0.97	0.69	0.20	40	10.0	0.4	22.0
0.55	0.15	0.04	31	5.6	0.7	5.2
0.53	0.22	0.39	3	6.5	2.0	1.4
0.36	0.09	0.03	17	8.7	0.7	16.0
0.62	0.02	0.05	45	9.2	0.9	6.8
0.31	0.01	0.04	21	7.3	1.3	5.7
0.76	0.13	0.05	32	7.4	0.9	6.5
0.43	0.05	0.29	50	14.6	0.7	4.7
0.31	0.01	0.04	6	7.0	1.4	6.3
0.21	0.02	0.11	3	8.5	2.0	1.8
0.11	0.01	0.01	11	9.5	1.7	3.1
0.61	0.03	0.02	8	8.5	2.6	1.6
0.15	0.11	0.02	15	8.3	2.1	4.4

Table A3: Coastal-Specific Data Rows

Photic Total Nitrogen mg/L	Photic Total Inorganic Nitrogen mg/L	Photic Total Phosphorus mg/L	Photic Chlorophyll a µg/L	Surface Dissolved Oxygen mg/L	Secchi Depth meters	Photic Turbidity NTU
0.21	0.10	0.02	56	8.0	4.8	3.8
0.32	0.06	0.05	25	9.4	1.4	2.5
0.11	0.02	0.02	32	8.0	3.0	1.1
0.40	0.11	0.04	44	8.3	1.2	7.8
1.06	0.72	0.19	4	6.9	0.6	60.0
0.31	0.06	0.02	38	8.2	1.7	9.8
0.21	0.01	0.02	38	7.6	0.8	4.7
0.37	0.02	0.02	20	8.0	0.8	10.0
0.51	0.03	0.02	40	10.0	0.8	4.7
0.33	0.07	0.03	32	10.5	1.6	5.0
0.33	0.05	0.01	16	8.5	2.9	2.0
0.61	0.19	0.04	34	10.3	1.5	2.8
0.41	0.02	0.04	40	11.8	1.4	3.3
0.46	0.09	0.06	7	6.2	1.1	15.0
0.25	0.01	0.02	50	14.1	0.7	10.0
1.22	0.56	0.07	40	7.9	0.3	7.5
0.41	0.04	0.03	39	8.3	0.4	8.3
0.39	0.02	0.02	25	7.5	1.0	2.1
0.69	0.20	0.03	1	6.1	0.5	5.2
0.61	0.02	0.04	57	7.5	1.9	7.2
0.21	0.04	0.05	3	7.2	1.9	2.2
0.30	0.01	0.03	46	9.3	0.6	16.0
0.57	0.02	0.04	51	9.0	1.2	11.0
0.41	0.07	0.03	10	8.2	2.1	2.1
0.21	0.08	0.03	40	7.7	2.2	5.4
0.61	0.06	0.18	11	8.5	0.5	6.6
0.53	0.06	0.11	30	8.9	0.5	8.0
1.42	0.15	0.18	30	4.4	0.3	11.0
1.41	0.03	0.01	23	8.7	0.3	23.0
0.39	0.14	0.02	9	7.9	1.1	1.1
0.41	0.02	0.08	24	9.4	0.5	18.0
0.21	0.01	0.05	26	8.3	2.6	4.7
0.21	0.05	0.01	1	7.7	3.0	0.4
0.06	0.04	0.03	1	7.5	1.3	1.7
0.51	0.02	0.11	42	8.2	0.5	9.3
0.40	0.01	0.01	16	8.2	0.9	10.0
0.21	0.06	0.04	1	6.0	1.9	6.8
0.46	0.02	0.03	38	6.3	1.3	3.9
0.21	0.02	0.01	10	9.0	2.3	3.0
0.79	0.24	0.03	26	7.6	0.8	7.2
0.31	0.05	0.01	36	8.0	3.5	1.0
0.11	0.02	0.02	1	7.3	1.9	1.7
0.91	0.05	0.15	31	5.8	0.4	7.8
0.31	0.06	0.02	36	7.7	2.4	5.2
0.45	0.03	0.05	16	7.2	0.4	18.0
0.86	0.18	0.25	29	7.0	0.5	5.2
1.71	0.03	0.02	26	8.7	0.3	25.0
0.63	0.02	0.05	24	8.9	0.4	11.0
0.31	0.04	0.07	20	7.2	1.8	15.0
0.71	0.02	0.08	34	7.8	0.5	6.2

Table A4: Southeastern Plain-Specific Data Rows

Photic Total Nitrogen mg/L	Photic Total Inorganic Nitrogen mg/L	Photic Total Phosphorus mg/L	Photic Chlorophyll a µg/L	Surface Dissolved Oxygen mg/L	Secchi Depth meters	Photic Turbidity NTU
0.11	0.01	0.01	5	8.0	2.1	1.7
0.21	0.02	0.05	1	5.9	1.6	3.5
0.21	0.02	0.03	5	7.1	1.5	5.9
0.21	0.02	0.01	10	9.0	2.3	3.0
0.21	0.03	0.03	3	7.8	2.0	2.3
0.21	0.03	0.05	11	7.7	1.1	1.8
0.21	0.05	0.01	9	8.1	2.5	1.7
0.21	0.06	0.01	3	7.7	1.7	4.2
0.21	0.06	0.01	48	6.7	1.1	15.0
0.29	0.02	0.02	5	7.7	1.9	1.8
0.31	0.02	0.03	23	8.2	0.5	16.0
0.31	0.03	0.03	6	7.1	2.0	2.0
0.31	0.03	0.02	13	5.6	1.5	1.6
0.32	0.13	0.01	4	5.2	2.0	2.0
0.35	0.02	0.02	15	7.9	1.3	6.6
0.35	0.07	0.05	30	8.0	1.0	7.3
0.36	0.08	0.07	9	6.7	1.0	2.7
0.36	0.09	0.03	9	5.6	1.5	2.6
0.38	0.07	0.04	5	4.5	1.0	8.5
0.39	0.01	0.04	24	8.1	0.4	26.0
0.40	0.02	0.02	7	7.6	2.1	3.5
0.40	0.27	0.01	3	4.8	1.0	1.3
0.41	0.03	0.03	4	3.3	1.3	2.7
0.41	0.03	0.05	8	6.7	1.5	3.2
0.41	0.04	0.03	39	8.3	0.4	8.3
0.42	0.07	0.02	23	7.6	2.7	5.8
0.43	0.04	0.05	53	8.8	0.8	9.2
0.44	0.29	0.01	8	7.8	1.6	1.0
0.45	0.03	0.04	8	4.7	1.1	4.2
0.46	0.30	0.08	44	7.8	0.7	14.0
0.47	0.06	0.06	20	6.8	0.7	20.0
0.51	0.03	0.07	51	7.0	0.8	6.4
0.51	0.05	0.02	8	8.2	0.9	3.4
0.51	0.06	0.08	14	5.2	1.0	4.7
0.51	0.06	0.08	76	7.1	0.7	6.0
0.52	0.07	0.02	3	5.3	1.7	2.1
0.53	0.04	0.04	19	5.0	1.0	6.1
0.53	0.06	0.02	12	6.6	1.0	3.5
0.54	0.02	0.06	31	4.7	0.6	11.0
0.54	0.08	0.06	12	9.2	0.9	7.9
0.56	0.13	0.07	5	3.3	0.7	4.8
0.58	0.11	0.08	4	2.5	1.2	5.0
0.59	0.13	0.11	4	3.5	0.8	1.8
0.61	0.02	0.12	10	7.4	0.8	3.6
0.61	0.06	0.13	38	6.2	0.8	4.6
0.66	0.20	0.12	50	8.8	0.6	16.0
0.67	0.35	0.04	12	10.2	0.5	12.0
0.81	0.03	0.05	23	8.7	1.9	2.1
0.81	0.25	0.23	21	4.9	0.4	12.0
0.83	0.10	0.24	82	3.1	0.5	15.0
0.86	0.07	0.03	13	8.6	1.6	2.5

Table A5: Blue Ridge-Specific Data Rows

Photic Total Nitrogen mg/L	Photic Total Inorganic Nitrogen mg/L	Photic Total Phosphorus mg/L	Photic Chlorophyll a µg/L	Surface Dissolved Oxygen mg/L	Secchi Depth meters	Photic Turbidity NTU
0.46	0.43	0.10	2	7.9	0.5	15.0
0.15	0.07	0.04	16	11.5	1.3	5.3
0.21	0.05	0.06	15	10.0	1.2	2.4
0.74	0.01	0.06	27	8.2	0.8	1.0
0.24	0.08	0.05	7	9.4	1.0	3.2
0.51	0.05	0.05	81	8.5	1.1	6.2
0.40	0.02	0.02	22	10.7	0.6	5.3
0.60	0.02	0.03	34	7.3	0.9	8.9
0.52	0.02	0.03	23	7.6	1.0	6.3
0.61	0.02	0.03	22	8.4	0.9	11.0
0.61	0.05	0.05	58	8.3	1.0	7.7
0.93	0.58	0.10	21	11.1	1.1	3.6
0.33	0.02	0.05	34	13.0	1.0	4.9
0.21	0.03	0.02	19	7.9	3.1	2.2
0.51	0.03	0.02	13	9.5	1.3	2.2
0.11	0.02	0.01	5	6.9	2.3	1.5
1.51	0.96	0.18	62	10.5	0.4	5.9
0.51	0.03	0.05	20	9.1	0.6	4.0
0.21	0.02	0.04	11	9.9	1.0	3.6
0.24	0.17	0.02	5	6.9	5.6	2.0
0.90	0.54	0.08	14	10.8	1.2	3.2
0.12	0.03	0.03	12	10.6	1.5	4.7
0.51	0.08	0.03	35	10.0	0.7	5.7
0.73	0.55	0.15	7	7.6	0.4	4.4
0.42	0.01	0.01	21	8.4	1.1	6.4
0.43	0.20	0.04	21	5.8	0.4	10.0
0.24	0.07	0.04	4	7.3	1.9	2.7
0.21	0.19	0.03	4	7.7	7.5	1.0
0.72	0.02	0.05	31	8.2	1.9	8.2
0.19	0.10	0.02	15	10.4	1.3	8.1
0.54	0.36	0.08	7	8.3	0.6	8.6
0.40	0.22	0.02	3	5.9	2.2	1.1
0.28	0.04	0.04	20	9.5	0.8	5.8
0.26	0.01	0.03	27	14.4	1.0	7.8
0.79	0.09	0.17	23	11.2	0.9	5.6
0.43	0.05	0.07	9	11.8	0.5	6.9
0.47	0.08	0.03	17	9.2	1.0	2.4
0.41	0.03	0.02	12	9.5	1.1	4.2
0.21	0.02	0.01	13	9.1	1.8	2.6
0.91	0.02	0.06	48	14.0	0.9	8.0
0.82	0.15	0.04	24	9.8	0.7	6.9
0.36	0.03	0.03	8	10.0	1.0	1.8
0.50	0.41	0.01	7	9.1	1.8	8.4
0.31	0.02	0.05	13	10.7	1.0	3.3
0.29	0.12	0.01	3	8.5	5.1	1.0
0.69	0.37	0.09	2	8.0	0.4	8.3
0.69	0.01	0.04	6	8.2	1.2	1.0
0.73	0.06	0.04	28	10.2	0.6	9.3
0.89	0.22	0.03	14	8.4	1.2	3.8
0.28	0.10	0.02	4	7.7	3.1	2.8

```
/* This program carries out the estimation and prediction routines for the */
/* technical report. Analysis steps follow the order of the report.        */

clear
# delimit;
set memory 500m;
set more off;
set maxvar 5000;
capture log close;
log using .out, text replace;
log off;

/* SUMMARY STATISTICS */
use excedata;
gen Ecat = (1*cat1 + 2*cat2 + 3*cat3 + 4*cat4 + 5*cat5)/100;
summ Ecat loutcome, detail;
summ Ecat loutcome if row < 51, detail;
collapse (mean) Ecat loutcome, by(row);
summ Ecat loutcome if row < 51, detail;
clear;

/* ORDERED LOGIT ESTIMATION */
use excedata;

* Full State Models
ologit loutcome tn tin tp chla do secchi turbid, vce(cluster expid);
ologit loutcome tn tp chla turbid, vce(cluster expid);
ologit loutcome tn tp chla secchi turbid, vce(cluster expid);

mfx, predict(p outcome(1)) eyex;
mfx, predict(p outcome(2)) eyex;
mfx, predict(p outcome(3)) eyex;
mfx, predict(p outcome(4)) eyex;
mfx, predict(p outcome(5)) eyex;

* Piedmont Model
ologit loutcome tn tp chla secchi turbid if expid<7|expid == 14, vce(cluster
expid);
mfx, predict(p outcome(1)) eyex;
mfx, predict(p outcome(2)) eyex;
mfx, predict(p outcome(3)) eyex;
mfx, predict(p outcome(4)) eyex;
mfx, predict(p outcome(5)) eyex;

* Blue Ridge Model
ologit loutcome tn tp chla secchi turbid if expid>6 & expid<10, vce(cluster
expid); /* blue ridge */
mfx, predict(p outcome(1)) eyex;
mfx, predict(p outcome(2)) eyex;
mfx, predict(p outcome(3)) eyex;
mfx, predict(p outcome(4)) eyex;
mfx, predict(p outcome(5)) eyex;

* Coastal Model
ologit loutcome tn tp chla secchi turbid if expid>10 & expid<14, vce(cluster
expid); /* Coastal */
```

```
mfx, predict(p outcome(1)) eyex;
mfx, predict(p outcome(2)) eyex;
mfx, predict(p outcome(3)) eyex;
mfx, predict(p outcome(4)) eyex;
mfx, predict(p outcome(5)) eyex;

/* BINOMIAL ESTIMATION */
clear;
use excedata;

* Statewide Models
collapse (mean) tn tin tp chla secchi do turbid cat1 cat2 cat3 cat4 cat5,
by(row);
keep if row < 51;
gen z = (1*cat1 + 2*cat2 + 3*cat3 + 4*cat4 + 5*cat5)/500;
gen lhs = log(z/(1-z));
reg lhs tn tin tp chla do secchi turbid;
reg lhs tn tp chla secchi turbid;
reg lhs tn tin tp chla do turbid;
reg lhs tn tp chla turbid;
clear;
use excedata;

* Peidmont and Plains Model
keep if expid<7|expid == 14;
collapse (mean) tn tin tp chla secchi do turbid cat1 cat2 cat3 cat4 cat5,
by(row);
gen z = (1*cat1 + 2*cat2 + 3*cat3 + 4*cat4 + 5*cat5)/500;
gen lhs = log(z/(1-z));
reg lhs tn tin tp chla secchi do turbid;
clear;
use excedata;

* Blue Ridge Model
keep if expid>6 & expid<10;
collapse (mean) tn tin tp chla secchi do turbid cat1 cat2 cat3 cat4 cat5,
by(row);
gen z = (1*cat1 + 2*cat2 + 3*cat3 + 4*cat4 + 5*cat5)/500;
gen lhs = log(z/(1-z));
reg lhs tn tin tp chla secchi do turbid;
clear;
use excedata;

* Coastal Model
keep if expid>10 & expid<14;
collapse (mean) tn tp chla secchi turbid cat1 cat2 cat3 cat4 cat5, by(row);
gen z = (1*cat1 + 2*cat2 + 3*cat3 + 4*cat4 + 5*cat5)/500;
gen lhs = log(z/(1-z));
reg lhs tn tp chla secchi turbid;
clear;

/* SUMMARY STATISTICS FOR FOCUS LAKES */
use nc_readings;

* North Carolina
collapse (median) tn tin tp chla secchi do turbidity (count) cnt=tn,
by(lake);
clear;
use sc_readings;
```

```
* South Carolina
collapse (median) tn tin tp chla secchi do turbidity (count) cnt=do,
by(lake);
clear;

/* BASELINE PREDICTIONS - ORDERED LOGIT MODEL  */

use excedata;
ologit loutcome tn tp chla secchi turbid, vce(cluster expid);
clear;
use nc_readings;

* NC median
collapse (median) tn tp tin chla do secchi turbidity, by(lake);
predict p1 p2 p3 p4 p5;
gen rhat = 1*p1 + 2*p2 + 3*p3 + 4*p4 + 5*p5;
save nc_median, replace;
clear;
use nc_readings;

/* NC distribution */
predict p1 p2 p3 p4 p5;
gen rhat = 1*p1 + 2*p2 + 3*p3 + 4*p4 + 5*p5;
collapse (mean) r_mean=rhat (median) r_median=rhat (count) r_count=rhat (iqr)
r_iqr=rhat, by(lake);
save nc_dist, replace;
clear;
use sc_readings;

/* SC distribution */
predict p1 p2 p3 p4 p5;
gen rhat = 1*p1 + 2*p2 + 3*p3 + 4*p4 + 5*p5;
collapse (mean) r_mean=rhat (median) r_median=rhat (count) r_count=rhat (iqr)
r_iqr=rhat, by(lake);
save sc_dist, replace;
clear;
use sc_readings;

* SC median
collapse (median) tn tp tin chla do secchi turbidity, by(lake);
predict p1 p2 p3 p4 p5;
gen rhat = 1*p1 + 2*p2 + 3*p3 + 4*p4 + 5*p5;
save sc_median, replace;
clear;

use excedata;
ologit loutcome tn tp chla turbid, vce(cluster expid);
clear;
use sc_readings;

collapse (median) tn tp tin chla do secchi turbidity, by(lake);
predict p1 p2 p3 p4 p5;
gen rhat = 1*p1 + 2*p2 + 3*p3 + 4*p4 + 5*p5;
save sc_median_r, replace;
clear;
```

```
/* BASELINE PREDICTIONS BINOMIAL MODEL */

clear;
use excedata;
collapse (mean) tn tin tp chla secchi do turbid cat1 cat2 cat3 cat4 cat5,
by(row);
keep if row < 51;
gen z = (1*cat1 + 2*cat2 + 3*cat3 + 4*cat4 + 5*cat5)/500;
gen lhs = log(z/(1-z));
reg lhs tn tin tp chla do secchi turbid;
clear;

/* NC distribution */
use nc_readings;
predict zhat;
replace zhat = exp(zhat)/(1+exp(zhat));
gen p1 = binomial(5,1,zhat);
gen p2 = binomial(5,2,zhat) - p1;
gen p3 = binomial(5,3,zhat) - p1 - p2;
gen p4 = binomial(5,4,zhat) - p1 - p2 - p3;
gen p5 = binomial(5,5,zhat) - p1 - p2 - p3 - p4;
gen rhat = 1*p1 + 2*p2 + 3*p3 + 4*p4 + 5*p5;
collapse (mean) r_mean=rhat (median) r_median=rhat (count) r_count=rhat (iqr)
r_iqr=rhat, by(lake);
save nc_dist_MK, replace;
clear;

/* NC median */
use nc_readings;
collapse (median) tn tp tin chla do secchi turbidity, by(lake);
predict zhat;
replace zhat = exp(zhat)/(1+exp(zhat));
gen p1 = binomial(5,1,zhat);
gen p2 = binomial(5,2,zhat) - p1;
gen p3 = binomial(5,3,zhat) - p1 - p2;
gen p4 = binomial(5,4,zhat) - p1 - p2 - p3;
gen p5 = binomial(5,5,zhat) - p1 - p2 - p3 - p4;
gen rhat = 1*p1 + 2*p2 + 3*p3 + 4*p4 + 5*p5;
save nc_median_MK, replace;
clear;

/* SC distribution*/
use sc_readings;
predict zhat;
replace zhat = exp(zhat)/(1+exp(zhat));
gen p1 = binomial(5,1,zhat);
gen p2 = binomial(5,2,zhat) - p1;
gen p3 = binomial(5,3,zhat) - p1 - p2;
gen p4 = binomial(5,4,zhat) - p1 - p2 - p3;
gen p5 = binomial(5,5,zhat) - p1 - p2 - p3 - p4;
gen rhat = 1*p1 + 2*p2 + 3*p3 + 4*p4 + 5*p5;

collapse (mean) r_mean=rhat (median) r_median=rhat (count) r_count=rhat (iqr)
r_iqr=rhat, by(lake);
save sc_dist_MK, replace;
clear;

/* SC median */
use sc_readings;
```

```
collapse (median) tn tp tin chla do secchi turbidity, by(lake);
predict zhat;
replace zhat = exp(zhat)/(1+exp(zhat));
gen p1 = binomial(5,1,zhat);
gen p2 = binomial(5,2,zhat) - p1;
gen p3 = binomial(5,3,zhat) - p1 - p2;
gen p4 = binomial(5,4,zhat) - p1 - p2 - p3;
gen p5 = binomial(5,5,zhat) - p1 - p2 - p3 - p4;
gen rhat = 1*p1 + 2*p2 + 3*p3 + 4*p4 + 5*p5;
save sc_median_MK, replace;
clear;

use excedata;
collapse (mean) tn tin tp chla secchi do turbid cat1 cat2 cat3 cat4 cat5,
by(row);
keep if row < 51;
gen z = (1*cat1 + 2*cat2 + 3*cat3 + 4*cat4 + 5*cat5)/500;
gen lhs = log(z/(1-z));
reg lhs tn tin tp chla do turbid;
clear;

use sc_readings;
collapse (median) tn tp tin chla do secchi turbidity, by(lake);
predict zhat;
replace zhat = exp(zhat)/(1+exp(zhat));
gen p1 = binomial(5,1,zhat);
gen p2 = binomial(5,2,zhat) - p1;
gen p3 = binomial(5,3,zhat) - p1 - p2;
gen p4 = binomial(5,4,zhat) - p1 - p2 - p3;
gen p5 = binomial(5,5,zhat) - p1 - p2 - p3 - p4;
gen rhat = 1*p1 + 2*p2 + 3*p3 + 4*p4 + 5*p5;
save sc_median_MK_r, replace;
clear;

/* 20% IMMPROVEMENT PREDICTIONS - ORDERED LOGIT MODEL  */

use excedata;
ologit loutcome tn tp chla secchi turbid, vce(cluster expid);
clear;
use nc_readings;
replace tn = tn*.8;
replace tp = tp*.8;
replace tin = tin*.8;
replace chla = chla*.8;
replace do   = do*1.2;
replace secchi = secchi*1.2;
replace turbidity = turbidity*.8;

* NC median
collapse (median) tn tp tin chla do secchi turbidity, by(lake);
predict p1 p2 p3 p4 p5;
gen rhat = 1*p1 + 2*p2 + 3*p3 + 4*p4 + 5*p5;
save nc_median_20, replace;
clear;
use sc_readings;
replace tn = tn*.8;
replace tp = tp*.8;
replace tin = tin*.8;
replace chla = chla*.8;
```

```
replace do   = do*1.2;
replace secchi = secchi*1.2;
replace turbidity = turbidity*.8;

* SC median
collapse (median) tn tp tin chla do secchi turbidity, by(lake);
predict p1 p2 p3 p4 p5;
gen rhat = 1*p1 + 2*p2 + 3*p3 + 4*p4 + 5*p5;
save sc_median_20, replace;
clear;

use excedata;
ologit loutcome tn tp chla turbid, vce(cluster expid);
clear;
use sc_readings;
replace tn = tn*.8;
replace tp = tp*.8;
replace tin = tin*.8;
replace chla = chla*.8;
replace do   = do*1.2;
replace secchi = secchi*1.2;
replace turbidity = turbidity*.8;

collapse (median) tn tp tin chla do secchi turbidity, by(lake);
predict p1 p2 p3 p4 p5;
gen rhat = 1*p1 + 2*p2 + 3*p3 + 4*p4 + 5*p5;
save sc_median_r_20, replace;
clear;

/* 20% IMPROVEMENT PREDICTIONS BINOMIAL MODEL */

clear;
use excedata;
collapse (mean) tn tin tp chla secchi do turbid cat1 cat2 cat3 cat4 cat5,
by(row);
keep if row < 51;
gen z = (1*cat1 + 2*cat2 + 3*cat3 + 4*cat4 + 5*cat5)/500;
gen lhs = log(z/(1-z));
reg lhs tn tin tp chla do secchi turbid;
clear;

/* NC median */
use nc_readings;
replace tn = tn*.8;
replace tp = tp*.8;
replace tin = tin*.8;
replace chla = chla*.8;
replace do   = do*1.2;
replace secchi = secchi*1.2;
replace turbidity = turbidity*.8;
collapse (median) tn tp tin chla do secchi turbidity, by(lake);
predict zhat;
replace zhat = exp(zhat)/(1+exp(zhat));
gen p1 = binomial(5,1,zhat);
gen p2 = binomial(5,2,zhat) - p1;
gen p3 = binomial(5,3,zhat) - p1 - p2;
gen p4 = binomial(5,4,zhat) - p1 - p2 - p3;
gen p5 = binomial(5,5,zhat) - p1 - p2 - p3 - p4;
gen rhat = 1*p1 + 2*p2 + 3*p3 + 4*p4 + 5*p5;
```

```
save nc_median_MK_20, replace;
clear;

/* SC median */
use sc_readings;
replace tn = tn*.8;
replace tp = tp*.8;
replace tin = tin*.8;
replace chla = chla*.8;
replace do   = do*1.2;
replace secchi = secchi*1.2;
replace turbidity = turbidity*.8;
collapse (median) tn tp tin chla do secchi turbidity, by(lake);
predict zhat;
replace zhat = exp(zhat)/(1+exp(zhat));
gen p1 = binomial(5,1,zhat);
gen p2 = binomial(5,2,zhat) - p1;
gen p3 = binomial(5,3,zhat) - p1 - p2;
gen p4 = binomial(5,4,zhat) - p1 - p2 - p3;
gen p5 = binomial(5,5,zhat) - p1 - p2 - p3 - p4;
gen rhat = 1*p1 + 2*p2 + 3*p3 + 4*p4 + 5*p5;
save sc_median_MK_20, replace;
clear;

use excedata;
collapse (mean) tn tin tp chla secchi do turbid cat1 cat2 cat3 cat4 cat5,
by(row);
keep if row < 51;
gen z = (1*cat1 + 2*cat2 + 3*cat3 + 4*cat4 + 5*cat5)/500;
gen lhs = log(z/(1-z));
reg lhs tn tin tp chla do turbid;
clear;

use sc_readings;
replace tn = tn*.8;
replace tp = tp*.8;
replace tin = tin*.8;
replace chla = chla*.8;
replace do   = do*1.2;
replace secchi = secchi*1.2;
replace turbidity = turbidity*.8;
collapse (median) tn tp tin chla do secchi turbidity, by(lake);
predict zhat;
replace zhat = exp(zhat)/(1+exp(zhat));
gen p1 = binomial(5,1,zhat);
gen p2 = binomial(5,2,zhat) - p1;
gen p3 = binomial(5,3,zhat) - p1 - p2;
gen p4 = binomial(5,4,zhat) - p1 - p2 - p3;
gen p5 = binomial(5,5,zhat) - p1 - p2 - p3 - p4;
gen rhat = 1*p1 + 2*p2 + 3*p3 + 4*p4 + 5*p5;
save sc_median_MK_r_20, replace;
clear;

/* EUTROMOD IMPROVEMENTS - ORDERED LOGIT MODEL  */
use excedata;
ologit loutcome tn tp chla secchi turbid, vce(cluster expid);
clear;
use eutro;
predict p1 p2 p3 p4 p5;
```

```
gen rhat = 1*p1 + 2*p2 + 3*p3 + 4*p4 + 5*p5;

/* EUTROMOD IMPROVEMENTS - BINOMIAL MODEL  */
clear;
use excedata;
collapse (mean) tn tin tp chla secchi do turbid cat1 cat2 cat3 cat4 cat5,
by(row);
keep if row < 51;
gen z = (1*cat1 + 2*cat2 + 3*cat3 + 4*cat4 + 5*cat5)/500;
gen lhs = log(z/(1-z));
reg lhs tn tin tp chla do turbid;
clear;
use eutro;
predict zhat;
replace zhat = exp(zhat)/(1+exp(zhat));
gen p1 = binomial(5,1,zhat);
gen p2 = binomial(5,2,zhat) - p1;
gen p3 = binomial(5,3,zhat) - p1 - p2;
gen p4 = binomial(5,4,zhat) - p1 - p2 - p3;
gen p5 = binomial(5,5,zhat) - p1 - p2 - p3 - p4;
gen rhat = 1*p1 + 2*p2 + 3*p3 + 4*p4 + 5*p5;

log close;
```