

Environmental Determinants of Lake Trophic Status in the Conterminous United States: A Data Mining Approach

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Abstract

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Introduction

Productivity in lentic systems is often categorized across a range of trophic states (e.g. the trophic continuum) from early successional (i.e. oligotrophic) to late successional lakes (i.e. hypereutrophic) (Carlson 1977). Lakes naturally occur across the range of trophic state and higher primary productivity is not necessarily a predictor of poor ecological condition. Lakes that are naturally oligotrophic occur in nutrient poor areas or have a more recent geologic history. These lakes are often found in higher elevations, have clear water, and are often favored for drinking water or direct contact recreation (e.g. swimming). Lakes with higher productivity (e.g. eutrophic lakes) have greater nutrient loads, tend to be less clear, have greater density of aquatic plants, and often support more diverse and abundant fish communities. Lakes will naturally shift to higher trophic states but this is a slow process. Given this fact, monitoring trophic state allows the identification of rapid shifts in trophic state or locating lakes with unusually high productivity (e.g. hypereutrophic). These cases are indicative of lakes under greater anthropogenic nutrient loads, also known as cultural eutrophication, and are more likely to be at risk of fish kills, fouling, and harmful algal blooms (Smith 1998; Smith, Tilman, and Nekola 1999; Smith et al. 2006).

Given the association between trophic state and many ecosystem services and disservices, being able to model trophic state could allow for estimating trophic state in unmonitored lakes and provide a first cut at identifying lakes with the potential for harmful algal blooms and other problems associated with cultural eutrophication. Most prior models related to

36 trophic state are either limited in spatial extent, have data from a small number of lakes,
37 model nutrients or chlorophyll a directly, or focus on in-lake information (i.e. nutrients) and
38 not on the landscape-level data. For instance, Imboden and Gächter (1978) built a model
39 of phosphorus using . This model... And xxx said this. Additionally... xxx found...

40 Building on these past efforts, we take advantage of one the first complete national scale
41 efforts monitoring lakes to try and discern broad patterns in both in-lake parameters that
42 drive trophic state and landscape level parameters that might also drive trophic state

- 43 • Our primary question is, at the national scale, what are the primary determinants of
44 lake trophic status?
- 45 • Can those determinants be used to predict trophic state with an acceptable level of
46 accuracy?

47 Determinants include, chemical and physical parameters of the lake water column and land
48 use/land cover. Lake trophic status defined by Chl a.

49 Methods

50 Data and Study Area

51 The two primary sources of data for this study are the National Lakes Assessment (NLA) data
52 and the National Land Cover Dataset (NLCD) (USEPA 2009). Both datasets are national in
53 scale and provide a unique snapshot view of the condition of United States' lakes and the
54 patterns of the lakes surrounding landscape.

55 The NLA data were collected during the summer of 2007 and the final data were released in
56 2009. With consistent methods and metrics collected at 1056 locations across the conterminous
57 United States, the NLA provides a unique opportunity to examine continental scale patterns
58 in lake productivity. The NLA collected data on biophysical measures of lake water quality
59 and habitat. For this analysis we primarily examined the water quality measurements from
60 the NLA [TABLE REF].

61 Adding to the monitoring data collected via the NLA, we use the 2006 NLCD data to examine
62 the possible landscape-level drivers of trophic status in lakes. The NLCD is a nationally
63 collected land use land cover dataset that also provides estimates of impervious surface. We
64 collected total land use land cover and total percent impervious surface within the surrounding
65 landscape of the lake. We defined the surrounding landscape of a lake with three different
66 buffer distances: 300 meters, 1500 meters, and 2500 meters. The various distances were used
67 to tease out differences in local landscape effects versus larger landscape-level effects.

68 Defining Trophic State

69 The dependent variable for this effort is lake trophic state. Trophic state is usually defined
70 over four levels: oligotrophic, mesotrophic, eutrophic, and hypereutrophic. Commonly, cut-off

values for each of these four levels may be specified with nitrogen concentration, phosphorus concentration, secchi depth, or chlorophyll a concentration (Carlson 1977; USEPA 2009). As this study is based largely from the NLA we use the NLA definition of trophic state based on the chlorophyll a concentrations (Table).

Trophic State	Cut-off
oligotrophic	≤ 0.2
mesotrophic	$>2-7$
eutrophic	$>7-30$
hypereutrophic	>30

Variable Selection

A strength of random forest is its ability to handle numerous correlated variables without a decrease in prediction accuracy. Yet the number of redundant correlated predictor variables in our data requires a cursory reduction through the described variable selection method. To do this we examine the correlation between log transformed chlorophyll a concentration and each of the log transformed variables. The rationale behind this selection method is to discard variables with little to no association with chlorophyll a and thus trophic state. Variables that explained less than 5% of the variance (i.e. a pairwise correlation of less than 0.22) were assumed to not be associated with chlorophyll a concentration and were removed from further consideration. Additionally, variables measuring different attributes of the same distribution (e.g. minimum, maximum or mean temperature) were selected based on the variable with the strongest correlation with chlorophyll a. Lastly, the remaining predictor variables that are highly correlated with one another should not be included in the initial set of variables passed to the random forest, unless specified by domain knowledge. As such we examine the pairwise correlations of these remaining variables and make a determination, as determined by knowledge of the system, as to which variables to retain.

Random Forest

As stated above, our goal is to explore relative variable importance in determination of lake trophic status. We selected random forest as our statistical analysis approach, because, among other reasons, random forest provides a robust measure of variable importance. Random forest is a machine learning algorithm that aggregates numerous decision trees in order to obtain a consensus prediction of the response categories. Bootstrapped sample data is recursively partitioned according to a given random subset of predictor variables and completely grown without pruning. With each new tree, both the sample data and predictor variable subset is randomly selected.

This randomization provides an intrinsic means to calculate out-of-bag (OOB) error and variables importance.

102 All random forest analysis was conducted using R's randomForest package; for more details
103 see Breiman (2001).

104 Variable Importance

- 105 • How to use for variable selection
- 106 • what we used to identify important variables

107 Predicted Trophic State

- 108 • How random forests makes final predictions,
- 109 • what we used to assess accuracy, etc.

110 Results

111 Summary Statistics

- 112 • Narrative summary.
- 113 • Table

114 Variable Selection

- 115 • Which variables were selected to include, and why, in the Random Forest.
- 116
- 117 • Table.
- 118 • Pairs plot of selected variables showing little/weak association between selected variables.

119 Random Forest

- 120 • Summary of Random Forest model (number of Params, total oob, etc.)

121 Variable Importance

- 122 • Narrative description of variables.
- 123 • Table of Variables with gini or percent explained.

124 Predicted Trophic State

- 125 • Summary stats of percent of lakes in each class
- 126 • Confusion matrix of predicted with actual.

Discussion

- What worked
- What didnt
- What are the determinants and why improtant
- How can this be expanded to other non-monitored lakes?
- What else can Trophic State tell us?
- Cyanobacteria association with?
- CDF Plots

Acknowledgements

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