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Annual precipitation regulates spatial and temporal drivers of lake water clarity

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Abstract. Understanding how and why lakes vary and respond to different drivers through time and space is needed to understand, predict, and manage freshwater quality in an era of rapidly changing land use and climate. Water clarity regulates many characteristics of aquatic ecosystems and is responsive to watershed features, making it a sentinel of environmental change. However, whether precipitation alters the relative importance of features that influence lake water clarity or the spatial scales at which they operate is unknown. We used a data set of thousands of northern temperate lakes and asked (1) How does water clarity differ between a very wet vs. dry year? (2) Does the relative importance of different watershed features, or the spatial extent at which they are measured, vary between wet and dry years? (3) What lake and watershed characteristics regulate long-term water clarity trends? Among lakes, water clarity was reduced and less variable in the wet year than in the dry year; furthermore, water clarity was reduced much more in high-clarity lakes during the wet year than in low-clarity lakes. Climate, land use/land cover, and lake morphometry explained most variance in clarity among lakes in both years, but the spatial scales at which some features were important differed between the dry and wet years. Watershed percent agriculture was most important in the dry year, whereas riparian zone percent agriculture (around each lake and upstream features) was most important in the wet year. Between 1991 and 2012, water clarity declined in 23% of lakes and increased in only 6% of lakes. Conductance influenced the direction of temporal trend (clarity declined in lakes with low conductance), whereas the proportion of watershed wetlands, catchment-to-lake-area ratio, and lake maximum depth interacted with antecedent precipitation. Many predictors of water clarity, such as lake depth and landscape position, are features that cannot be readily managed. Given trends of increasing precipitation, eliminating riparian zone agriculture or keeping it <10% of area may be an effective option to maintain or improve water clarity.

Key words: land use; landscape ecology; land–water interactions; precipitation; remote sensing; water quality.

Introduction

Understanding how and why lakes vary and respond to different drivers through time and space is needed to understand, predict, and manage freshwater quality in an era of rapidly changing land use and climate. Watershed composition and configuration can influence surface water quality at multiple spatial scales (Allan et al. 1997, Tabacchi et al. 1998, Gergel et al. 1999, Tong and Chen 2002, Lee et al. 2009). Both whole watershed and riparian zone characteristics can affect surface water conditions (Correll 1996, Liu et al. 2003), but evidence for the relative importance of features measured at these different spatial scales is mixed. Some research shows that riparian buffer zones protect agricultural streams from degradation (Schlosser and Karr 1981, Debano and Schmidt 1990), but other research shows that upland land use can be just as important as riparian land use (Omernik et al. 1981). The strength and scale of land–water interactions is also affected by ecosystem-specific features, such as depth or position in hydrological flow paths (e.g., Kratz et al. 1997, Soranno et al. 1999, Read et al. 2015). However, the relative importance of features measured at different spatial scales and in-lake characteristics is not well understood because few studies consider variation over large, macrosystem-scale spatial gradients (Heffernan et al. 2014). Additionally, the role of variable climatic conditions in modulating watershed influences on surface waters is poorly understood because most studies do not consider interannual variation in climate (Townsend and Riley 1999, Whitehead et al. 2009).

As a component of overall climate conditions, interannual variation in precipitation may modulate the strength and spatial scales of land–water interactions by regulating hydrologic connectivity between lakes and their watersheds (Martin and Soranno 2006, Fraterrigo and Downing 2008). Drought conditions can weaken linkages, while heavy precipitation can strengthen linkages (Schindler et al. 1996, Webster et al. 2000, Williamson et al. 2014). Run-off and

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infiltration increase in wet years, potentially strengthening land–water connections (Bronstert et al. 2002, Sophocleous 2002, Whitehead et al. 2009). Therefore, watershed-level features may become more important than riparian zone features as precipitation enables broad-scale features to overwhelm fine-scale riparian features. Characteristics such as land use and land cover, lake and watershed morphometry, run-off potential, and surficial geology may also be relatively more important in explaining variability in wet years. However, wet conditions may also have a homogenizing effect on lake water quality, shrinking lake distributions and thereby making all watershed features less predictive (e.g., Webster et al. 2000). Additionally, wet conditions may increase the importance of riparian zone features as they become more important in regulating run-off from the watershed. In this study, we explore variation over space and time in a large sample of north temperate lakes using water clarity as an indicator of water quality.

Assessing if and how precipitation regulates watershed controls on lake water clarity requires measurements over broad spatial extents. Satellite remote sensing of inland waters provides the ability to characterize water clarity in thousands of lakes over broad geographical ranges. Early research demonstrated the utility of Landsat imagery to classify lakes by trophic status and characterize water clarity (Scarpace et al. 1979, Lillesand et al. 1983). Algorithm refinement has enabled accurate estimation of water clarity (i.e., Secchi disk depth) over thousands of lakes throughout the Midwest and Eastern United States (Kloiber et al. 2002, Chipman et al. 2004, Peckham and Lillesand 2006, Olmanson et al. 2008, 2013, Courville et al. 2014). These remotely sensed observations have been used to identify some predictors of lake water clarity over space and time. For example, in Maine, USA, light timber harvesting and wetland area had negative effects on lake clarity, while lake depth and watershed slope were positively correlated with Secchi depth (McCullough et al. 2012, 2013). In the Midwest Unitec States, small, shallow lakes in watersheds with high agricultural land use have been associated with low water clarity and declining trends over time (Olmanson et al. 2008, 2013). Overall, these findings provide an insight into some drivers of variation in water clarity across the landscape and through time, but they do not include a comprehensive list of watershed features, account for interannual changes in precipitation, nor quantify drivers at multiple spatial scales (e.g., riparian zone vs. whole watershed).

We used a data set of thousands of north temperate lakes and asked (1) How does water clarity differ between a very wet vs. dry year? (2) Does the relative importance of different watershed features, or the spatial extent at which they are measured, vary between wet and dry years? (3) What lake and watershed characteristics regulate long-term water clarity trends? Between dry and wet years, we hypothesized that watershed-wide land cover/land use characteristics including the percent agriculture would explain the most variance among lake water clarity in the wet year, while riparian zone agriculture would explain more variance in the dry year due to greater terrestrial-aquatic connectivity when precipitation was low. Similarly, we hypothesized that watershed and riparian characteristics such as land use/land cover, surficial geology, run-off potential, and watershed morphometry would explain more variation in clarity among lakes in the wet year, while lake morphometry and water chemistry characteristics would be more predictive of variation in clarity during the dry year. We hypothesized that land use/land cover features such as percent agriculture would be important predictors of long-term clarity trends.

Study area

This study was conducted in Wisconsin (USA), which encompasses about 145000 km^2, contains over 15000 lakes, and typifies the Upper Great Lakes region. Except for the ~35000 km^2 driftless region in southwestern Wisconsin, the state was glaciated and is characterized by flat topography. The climate is continental, with cold snowy winters and mild summers; most lakes are ice covered from late November to late March. Annual total precipitation can range 521–1049 mm (mean = 797 mm, standard deviation = 102 mm), and mean annual temperatures can range from 5.0° to 7.4°C (mean = 5.9°C, standard deviation = 0.9°C; Moran and Hopkins 2002, NOAA 2015). Northern Wisconsin is covered by extensive forests that regenerated following early 20th-century timber harvests. Presettlement vegetation in southern Wisconsin was characterized by prairie and savanna vegetation, but these were cleared in the late 1800s for agriculture (Curtis 1956, Carpenter et al. 2007). Agriculture, including row crops (primarily corn and soybeans) and dairy farms, remains dominant today. The major population centers are located in southeastern and south-central Wisconsin (Milwaukee and Madison, respectively). Our analysis included lakes in four ecoregions (Omernik and Gallant 1987): Northern Lakes and Forests (Ecoregion 50); North Central Hardwood Forests (Ecoregion 51); Driftless Area Ecoregion 52); and Southeastern Wisconsin Till Plains (Ecoregion 53). These ecoregions capture the most important land use and environmental characteristics that affect aquatic ecosystems and were derived from soils, land use, land-surface form, and potential natural vegetation maps.

Methods

Estimating water clarity

For this study, we used a database of remotely sensed lake Secchi depth estimates measured from 1991 to 2012 as a measure of water clarity. Secchi depths were estimated from Landsat data covering the state of Wisconsin. Data were downloaded from the Landsat Archive of the USGS EarthExplorer for Level 1T GeoTIFF data over a date range from 1 June to 30 September of each year. Images were used if they contained <50% cloud cover. Images were reprojected to the Wisconsin Transverse

Mercator coordinate system, and clouds, land, and optically shallow waters and aquatic vegetation were removed by an unsupervised classification system. Images acquired on the same day were combined to a single image mosaic. No explicit atmospheric corrections were made, however the empirical approach described here generates a unique regression equation for each date and scene. Therefore, the atmospheric conditions from each flyover day are implicit within each individual regression equation (see also Appendix S1: Table S1). Scan line correction failures were masked out when applicable.

In situ measurements of Secchi disk depth were used to calibrate remotely sensed imagery. In situ data were collected with the support of Wisconsin Citizen Lake Monitoring Network volunteers and were accessible through the Wisconsin Department of Natural Resources Surface Water Integrated Monitoring System (SWIMS). In situ measurements were used if they were made within 7 d of satellite overpasses. Stations on lakes greater than 2 ha in size were identified for each image mosaic and the spectral radiance values for these stations were extracted and used to calibrate a model (Eq. 1) for the satellite retrieval of water clarity.

$$\ln(\mathrm{SD}) = a + b\left(\frac{\mathrm{TM1}}{\mathrm{TM3}}\right) + c * \mathrm{TM1} \quad (1)$$

where SD is the estimated Secchi disk depth, *a*, *b*, and *c* are regression coefficients, and TM1 and TM3 are Landsat 5 blue (450–520 nm) and red (630–690 nm) bands, respectively. In the case of Landsat 7, ETM+ bands 1 (450–520 nm) and 3 (630–690 nm), were used. The form of this model has previously been implemented by others (Fuller et al. 2004, Brezonik et al. 2007, McCullough et al. 2012, Olmanson et al. 2013).

Water clarity estimates were restricted to the months of June through September, consistent with other studies (Olmanson et al. 2008), and when water clarity is generally lowest, lakes are ice-free, and citizen science monitoring programs were active. However, our study does not address within-season variability in water clarity, as the number and timing of measurements is not standardized among lakes. We estimated an annual summer average Secchi depth for any lake that had multiple measurements in a given year.

Comparing dry and wet years

To answer how water clarity differed between a very wet and dry year (Question 1) we compared predictors of water clarity during the driest year (2005) and the wettest year (2010) for which a substantial number of lakes had water clarity estimates in both years. We used only a single wet and dry year because the number of lakes observed by satellite varied among years. For example, increasing the number of years to the two wettest and two driest would have decreased the sample size by over an order of magnitude. A small number (n = 6) of outliers were identified that had extremely different water clarity values between the wet and dry year, resulting in 5002 lakes. The year 2005 was in the lowest quartile of long-term precipitation records; the state received 72.5 cm of precipitation (Fig. 1). The year 2010 was in the highest quartile and was the second wettest year on record; the state received 991 mm of precipitation (Information 2015). The long term mean precipitation (1895–2013) was 796 mm of precipitation. Despite large differences in precipitation, difference in annual mean temperature was small (7.3°C in 2005 and 7.5°C in 2010).

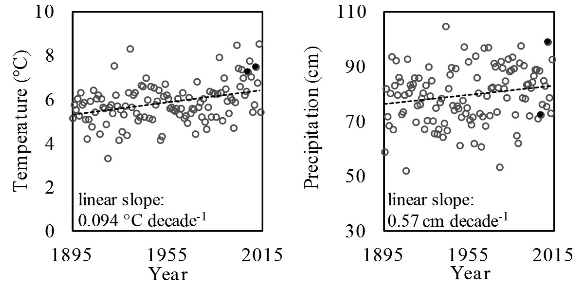

FIG. 1. Long-term calendar year records of temperature and precipitation in Wisconsin, USA, show that both are increasing. Black dots indicate temperature and precipitation conditions during the dry (2005) and wet (2010) years examined in our spatial analysis.

Predictor variables and spatial extents

To address the relative importance of different watershed features and the spatial extents at which they are measured (Question 2), we included seven predictor categories, including (1) measurements of land use/land cover, (2) surficial geological characteristics, (3) run-off potential, (4) watershed morphometry, (5) lake morphometry, (6) water chemistry, and (7) climate (temperature, precipitation). To assess multiple spatial extents, we estimated watershed morphometry, land use/land cover, run-off potential, and surficial geological characteristics at three scales. These included measurements in a 60-m riparian zone around each lake (called the local riparian zone), in a 60-m riparian zone around each lake and all upstream features (called the extended riparian zone), and in the entire watershed that drained to each lake (Fig. 2). The 60-m riparian zone width was chosen for consistency with the Great Lakes Aquatic GAP spatial framework (Brenden et al. 2006). Spatial and attribute data and detailed metadata for all predictor variables are available online (see Supplemental Information for more information).

Land use/land cover.—Land use/land cover data from 2006 were organized into ten classes as percent of total area for each spatial extent. Eight of these classes were based on combinations of existing classes listed in the National Land Cover Database (NLCD, Fry et al. 2011), including agriculture (a combination of pasture/hay and cultivated crops classes), grasslands (a combination of grassland/herbaceous and shrub/scrub classes), urban (a

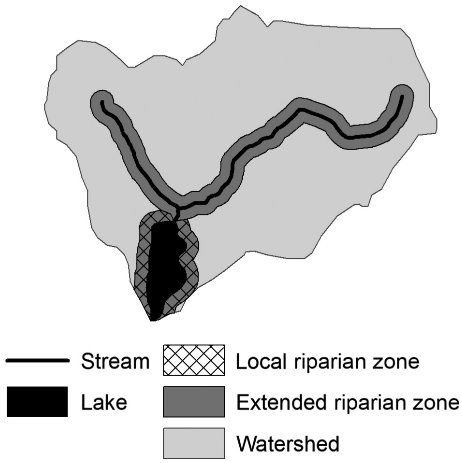

FIG. 2. The importance of watershed characteristics was assessed at three scales: an immediate 60-m riparian zone around each lake (cross-hatch area); a 60-m riparian zone around each lake and all upstream features (dark gray area); and the entire watershed draining into each lake (light gray area).

combination of low, medium, and high intensity developed classes), wetlands (a combination of woody and emergent herbaceous wetland classes), forest (a combination of deciduous, mixed, and conifer forest classes), open water, urban/suburban grass (developed, open space), and barren land. Impervious cover was estimated as the area-weighted average of percent imperviousness associated with each urban class in the NLCD. Artificial drainage was estimated as the spatial coincidence of poorly drained soils with agricultural land cover.

Surficial geology.—Surficial geological characteristics from the Quaternary Geological Atlas of the U.S. were aggregated into six categories: coarse, medium, fine, colluvium, alluvium, and no landform (peat and muck) for each of the three spatial extents (*data available online*).[4] Colluvium describes soils that form at the base of steep hillsides from unconcentrated surface run-off. Alluvium describes soils that have been eroded and redeposited by moving water.

Run-off potential.—Adjusted soil permeability was calculated from soil permeability (NRCS State Soil Geographic Data Base, *available online*)[5] and impervious cover with the equation (soil permeability) × ((100 − % impervious)/100). Run-off curve number was determined from combinations of NLCD land cover and soil hydrologic group (Soil Survey Staff 2015) per methods described by the Natural Resources Conservation Service (1986).

Watershed morphometry.—Watershed morphometry characteristics included the watershed-to-lake-area ratio, the landscape position of each lake (Kratz et al. 1997), and the percentage of area that was localized depressions in the watershed (1- and 5-m "sinks"). Localized depressions can correlate with wetlands not delineated with the NLCD and are an important predictor of dissolved organic carbon concentration (Winn et al. 2009), which can regulate water clarity (Morris et al. 1995). The slope and area were estimated for each of the three spatial extents.

Lake morphometry.—Lake morphometry characteristics included whether the lake had a dam or not (i.e., was at least partially artificial), the lake area, and the maximum and mean depth. We had maximum depth on 3991 of the lakes and mean depth on 1342 lakes.

Water chemistry.—Water chemistry characteristics of alkalinity (mEq/L), conductance (μS/cm), and pH were available for 4461, 4464, and 4684 lakes, respectively. All water chemistry characteristics were measured during the period 1970–2009. Lake specific observations that were sampled at multiple points in time were averaged to generate a single value for each lake.

Climate.—Both temperature and precipitation records were considered and aggregated over several different time scales. Records were interpolated from regional weather stations to each lake's watershed (data *available online*).[6] Precipitation records included the annual mean total long-term precipitation (1960–2012), the total precipitation over the "water year" (from October of previous year through September of sample year, either 2005 or 2010), and the total precipitation during spring months (April, May, June). Temperature was expressed as a proportion of the long-term mean because temperature exhibited a strong latitudinal trend that covaried with land use and land cover. We calculated the difference between the long-term mean and the mean daily temperature of the sample year (2005 or 2010), the preceding year (2004 or 2009), the spring temperature, and the temperature during the water year.

Statistical analyses

The R statistical software environment (R Core Team 2015) was used for all analyses. A t test was used to compare the populations of lake water clarities between the wet and dry years. To explore how lakes behaved in the wet year compared with the dry year, a segmented regression approach was used to test for the significance and position of break points in the relationship between Secchi disk depths for the dry and wet year (Muggeo 2003). Given a regression model between Secchi disk depths for the dry and wet years, this method minimizes the sum of squares of the differences between the observed and predicted dependent variable by incorporating the possibility of a breakpoint in the data, which

[4] http://gec.cr.usgs.gov/data/quatatlas/index.shtml
[5] http://water.usgs.gov/lookup/getspatial?ussoils
[6] http://daymet.ornl.gov/

results in a separate linear relationship between the independent and dependent variables across different ranges of the independent variable. Here, this method tested if the relationship between water clarity in the dry and wet year were different across the range of clarities and, if they were, what the breakpoint water clarity measure was.

A Random Forest algorithm (randomForest R package; Breiman 2001, Liaw and Wiener 2002) was used to assess the importance of each predictor in explaining variation in estimated water clarity among lakes in either the dry year or wet year as well as the difference in water clarity between these years. The algorithm is a nonparametric machine learning classification and regression tree analysis procedure that combines many randomized regression trees to improve prediction accuracy. The approach can handle a large number of predictor variables, is relatively insensitive to predictor variable distributions and covariance, and does not require interaction terms be explicitly defined (Cutler et al. 2007, Archer and Kimes 2008). The algorithm generates a large number of individual regression trees using random subsets of the data set and tree accuracy is assessed by estimating the mean squared error (MSE) using the data not selected to generate each tree. Averaged MSE estimates over all trees (the "forest") provide an estimate of overall model fit and is expressed as a percent of explained variance in the response variable. Output from the algorithm includes the percent variance explained by all predictors. Random Forest estimates of individual predictor variable importance can vary slightly between runs. Therefore, we ran diagnostics on the algorithm to construct an optimized number of trees (5000) above which predictor variable importance ranking was stable. We report the percent variance explained and standard error associated with different categories of predictors from 10 algorithm runs.

Additionally, we used the Random Forest algorithm to identify the top 20 predictors (top 25%). We used these top predictors in a classification and regression tree (CART) analyses to visualize an importance ranking of predictors. CARTs were applied to predictors of estimated water clarity among lakes in either the dry year or wet year as well as the difference in water clarity between these years. Differences in water clarity were calculated as a percent change from the first year (2005, the dry year) to the second year (2010, the wet year). CARTs were nonparametric conditional regression trees (Hothorn et al. 2006). These trees provided rankings of the top predictors of variation in water clarity and tree splits determined threshold values at which predictors at lower tree levels were organized. The top three levels of trees are reported. For all reported tree splits, $P < 0.01$. Separate Random Forest and CART analyses on lakes in Ecoregion 50 (Northern Lakes and Forests; $n = 3618$) and Ecoregions 51–53 (North Central Hardwood Forests, Driftless Area, and Southeastern Wisconsin Till Plains; $n = 1384$) were also conducted and are presented in the Appendix S1.

Temporal trends

We fit a linear mixed effects model (LMER; lme4 package in R; Bates et al. 2015) to evaluate temporal trends in water clarity (Question 3). This approach models log(Secchi depth) as a function of year, antecedent precipitation, several lake and watershed characteristics, interactions between selected variables, and random effects of lake identity on the intercept and year effect. The response variable in this model is an individual water clarity estimate rather than an annual average to allow the model to control for variable antecedent precipitation among estimates within each year. For this analysis, we used 72019 individual water clarity estimates made over the period 1991–2012 from 4843 lakes that had maximum depth and conductance estimates. This population of 4843 represents a subset of the lakes used in the comparison of wet and dry years.

In this model, an interaction between year and another predictor variable describes the effect of that predictor variable on the temporal trend in water clarity. An interaction between antecedent precipitation and another predictor variable describes the effect of that predictor variable on the response of water clarity to antecedent precipitation. Random effects characterize how each lake's mean water clarity estimate and temporal trend differs from the average lake after accounting for the fixed effects.

For each water clarity observation, we calculated antecedent precipitation as the average daily precipitation in the lake's watershed over a period that we expected to influence water clarity. This period was estimated as one hydraulic residence time of the lake prior to the water clarity estimate. Hydraulic residence time was estimated as V/Q, where V is lake volume and Q is outflow discharge, estimated from regression-based flow models (Diebel et al. 2014). In seepage lakes, this period is from 1 October of the previous year through the date of the water clarity estimate.

To minimize predictor covariance, we used a limited number of lake and watershed characteristics in the LMER model based on hypothesized controls on trends and results from our wet year vs. dry year comparison. Predictors included watershed wetlands, agriculture, and permeability, lake catchment to area ratio, maximum depth, and conductance. All variables were transformed to approximate normal distributions and converted to z scores to normalize coefficients for comparison among predictors.

We used a bootstrap method to evaluate the statistical significance of temporal trends for individual lakes. Each bootstrap iteration entailed sampling from the data with replacement for each lake and refitting the model. 95% confidence intervals for the temporal trend of each lake were estimated from the 0.025 and 0.975 quantiles of the distribution of estimated random effects.

Results

Question 1: Water clarity in dry vs. wet year

Across the population of 5002 lakes, water clarity was lower in the wet year (median = 2.37 m, interquartile

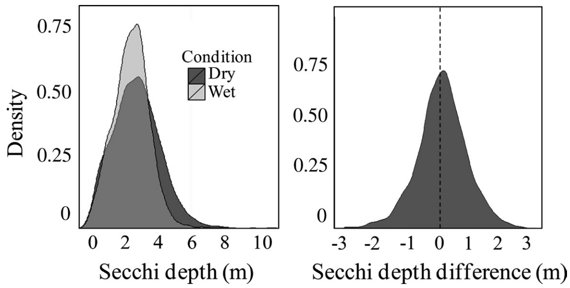

FIG. 3. Density histograms showing distributions of water clarity estimates (left) for 5002 lakes measured in both 2005 (dry year) and 2010 (wet year) and the distribution of water clarity differences between the dry and wet year (right).

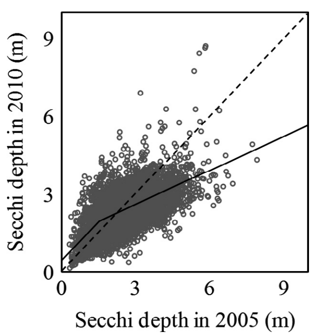

FIG. 4. Relationship between water clarity estimates for 2010 (wet year) and 2005 (dry year). There was a break point in the relationship between water clarity estimates in the dry year and the wet year at a Secchi depth of 1.52 m; below this threshold depth, the slope between water clarity in dry and wet years was 0.97, while above it, the slope was 0.44. Black lines indicate segmented regressions; dashed line indicates 1:1.

range = 1.85 m) compared with the dry year (median = 2.55 m, interquartile range = 1.81 m; t_{stat} = 12.45, P < 0.001). The distributions of clarity estimates between the two years were also different between the wet and dry years (Fig. 3). Clear lakes varied much more between the wet and dry years than low-clarity lakes. For example, whereas the median lake only changed by 0.18 m, lakes with high water clarity (Secchi depths > 3.5 m; n = 927) had a median Secchi depth of 3.96 and 2.94 m in the dry vs. wet year, a difference of 1.12 m.

Segmented regression identified a break point in the relationship between water clarity estimates in the dry year vs. the wet year at a Secchi depth of 1.52 ± 0.08 m (mean ± SD) (Fig. 4). Below this threshold depth, the slope between water clarity estimates in dry and wet years was 0.97, while above it, the slope was 0.44. The fact that the slope was very close to 1 at low water clarities indicates that clarity was insensitive to differences in precipitation between the dry and wet year in low clarity lakes, while the slope of 0.44 at higher water clarities indicates that clearer lakes were sensitive to differences between the wet and dry years. Indeed, while more lakes had poor water clarity (<2.5 m Secchi depths) in the wet year (n = 2823, 56%) compared with the dry year (n = 2406, 48%), substantially more lakes had high water clarity (>3.5 m Secchi depths) in the dry year (n = 927, 19%) than in the wet year (n = 330, 7%).

TABLE 1. All predictor categories except for surficial geology explained more variance in dry year than in wet year.

	Variance explained (%)	
Predictor category	Dry year (2005)	Wet year (2010)
Climate	29.3 ± 0.6	22.4 ± 0.5
Land use/land cover	28.7 ± 0.6	22.1 ± 0.5
Lake morphometry	27.3 ± 0.7	22.7 ± 0.5
Run-off potential	19.0 ± 0.2	12.3 ± 0.8
Watershed morphometry	18.0 ± 0.6	12.4 ± 0.4
Water chemistry	13.1 ± 1.0	2.7 ± 0.8
Surficial geology	3.6 ± 0.7	4.4 ± 0.6
Total	62.9 ± 1.5	54.1 ± 2.2

Note: Values presented are mean ± standard errors.

Question 2: Predictors and spatial extends regulating water clarity in dry vs. wet year

All predictor categories except for surficial geological characteristics were more predictive of variation in water clarity in the dry year compared with the wet year (Table 1). Predictor categories can be ordered based on their ability to explain variance in water clarity. The top group, which explained 27.3–29.3% of variance in the dry year and 22.1–22.7% of variance in the wet year included climate, land use/land cover, and lake morphometry. There were two categories that had low explanatory power: water chemistry and surficial geology. While water chemistry explained 13.1% of variance in the dry year, it explained only 2.7% of variance in the wet year; this difference between the wet and dry years was the largest of all predictor categories. Surficial geology explained only 3.6% and 4.4% of variance in the dry and wet year, respectively. Using all predictors, 62.9% of variance was explained in the dry year and 54.1% was explained in the wet year (Table 1).

In the dry year, percent agriculture in the watershed was the top predictor of water clarity and was negatively correlated with clarity. Lakes in watersheds with more than 21.6% agriculture had lower water clarity depths (median Secchi = 1.75, n = 1051) than lakes in watersheds with a percent agriculture below this threshold (median Secchi = 2.74, n = 3951; Fig. 5). In watersheds with low percent agriculture, maximum depth was the next most important predictor, with deep lakes having higher water clarity. In watersheds with high percent agriculture, percent agriculture in the extended riparian zone (a 60-m riparian zone around each lake and all upstream features) was the next more important predictor, with lakes that had a high percent agriculture having lower water clarity. Conductance, landscape position, and maximum depth made up the third level of the regression tree. Overall, the clearest lakes were ones with a low percent watershed agriculture, high depth, and a position high in the landscape (median Secchi = 3.39, n = 989). The lowest clarity

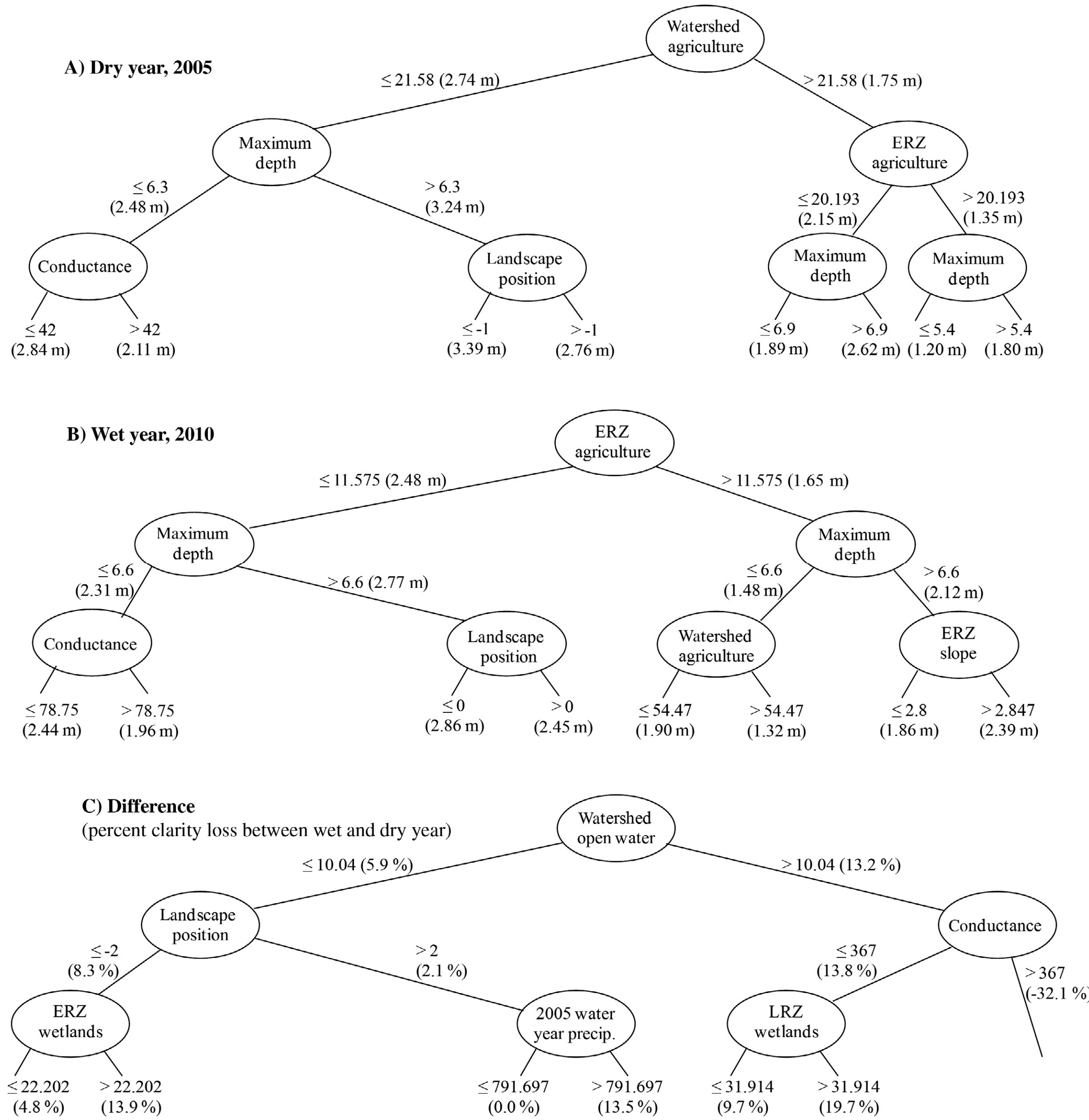

FIG. 5. Regression trees. Values in parentheses indicates the median Secchi depth for the corresponding tree split (A and B) or the percent clarity loss between the dry and wet year (C). "LRZ" stands for local riparian zone, which is a 60-m zone around each lake, and "ERZ" stands for the extended riparian zone, which is a 60-m zone around each lake and all upstream features. The values outside the parentheses refers to the variable value dictating the tree split

lakes were ones with a high percent watershed agriculture, a high percent agriculture in the extended riparian zone, and a shallow depth (median Secchi = 1.20, n = 251).

In the wet year, percent agriculture in the extended riparian zone was the top predictor of water clarity and was negatively correlated with clarity. Lakes with extended riparian zones having >11.6% agriculture had lower water clarity (median Secchi = 1.65 m, n = 865) than lakes below this threshold (median Secchi = 2.48, n = 4137; Fig. 5). At the next tree level, maximum depth was important both when the percent extended riparian zone agriculture was low and high. Conductance, landscape position, percent agriculture in the watershed, and the slope of the extended riparian zone made up the third level of the regression tree. Overall, the clearest lakes in the wet year were ones with a low percent agriculture in the extended riparian zone, high maximum depth, and a position high in the landscape (median Secchi = 2.86, n = 988). The lowest clarity lakes were ones with a high percent agriculture in the extended riparian zone, shallow depth, and a high percent of agriculture in the watershed (median Secchi = 1.32, n = 271).

Regression tree analyses showed that many of the top predictors of water clarity were found in the top three levels of trees for both the dry and wet years (Fig. 5). The percent agriculture in both the whole watershed as well as the extended riparian zone, maximum depth, conductance, and landscape position were five of the seven predictors in the top three tree levels. Many predictors were also in the same level in both trees. For example, maximum depth, conductance, and landscape position were found in levels two and three in both trees. In contrast, the relative position of the percent watershed agriculture and percent agriculture in the extended riparian zone differed between the dry and wet years. In the dry year, the percent watershed agriculture was the most important predictor, followed by the percent of agriculture in the extended riparian zone. In contrast, in the wet year the percent agriculture in the extended riparian zone was most important and the percent agriculture in the whole watershed was at the third level in the tree.

The percent open water in the watershed was the top predictor of the percent difference in water clarity between the dry year and wet years (Fig. 5). Lakes with a watershed percent open water >10.0% decreased in clarity by 13.2% (n = 2407), while lakes with a watershed percent open water below this threshold decreased 5.9% (n = 2595). At the next tree level, landscape position was important when the percent watershed open water was low and conductance was important when the percent watershed open water was high. The percent wetlands in the extended riparian zone, the precipitation in the 2005 water year (the dry year) for each watershed, and the percent wetlands in the immediate riparian zone made up the third level of the regression tree. Overall the lakes that experienced the largest drops in water clarity between the dry year and wet year were ones where the percent watershed open water was high, conductance was low, and the percent wetlands in the immediate riparian zone was high (19.7% change, n = 956). One group of lakes actually increased in clarity between the dry year and wet year: lakes where the percent watershed open water was high and conductance was high (−32.1% change, n = 49).

Question 3: Temporal trends

The LMER model showed that lake clarity has generally declined after controlling for effects of antecedent precipitation. Out of 4843 lakes, water clarity declined in 1124 (23.2%) and increased in only 281 (5.8%) lakes. The only variable that influenced the direction of the trend was conductance; lakes with lower conductance had the strongest decreasing trend in clarity. Three variables (percent watershed wetlands, catchment-to-lake-area ratio, and lake maximum depth) interacted with antecedent precipitation. In lakes with low watershed percent wetland or small catchment-to-lake-area ratios, water clarity declined by ~50% when antecedent precipitation was high. If watershed percent wetlands or catchment-to-lake-area ratios were high, lakes were insensitive to antecedent precipitation. Finally, deeper lakes were more responsive to precipitation than shallow lakes.

Discussion

Annual precipitation modulated both the dominant features as well as the spatial extents at which features regulated variability in lake water clarity, but in ways contrary to our hypotheses. All but one predictor category explained less variance in water clarity in the wet year than in the dry year. Further, riparian zone features were more important than watershed features in wet years, while the opposite was true in dry years. We attribute these results to several factors.

The lower explanatory power of lake and watershed features in the wet year is likely because lake water clarity was much more homogenous during the wet year and thus the distribution of water clarities was much more compressed (Fig. 3). A smaller response distribution means that it is more difficult to predict difference in clarity among lakes in the population. For spatial extents, we expected that during wet conditions, which should facilitate greater hydrologic connectivity between lakes and their watersheds (Martin and Soranno 2006, Fraterrigo and Downing 2008), whole watershed features would be more important than riparian zone features. The results show, however, that whole watershed features were more important in the dry year. There are multiple potential explanations for this unexpected result. Compared with wet years, surface water nutrient, sediment, and CDOM loading is greatly reduced and represents a smaller explanatory gradient across lakes. Consequently, other internal factors such as accumulation of previous loads and land-use legacies (Foster et al. 2003, Allan 2004) or water level change, and external factors such as nutrient loading from groundwater, may have a disproportionate influence on water clarity in dry years, especially if these are also strongly correlated with the watershed predictors. In contrast, the importance of riparian zone features in the wet year implies that riparian zone features will likely become more important in future years as precipitation is trending upwards in this region (Fig. 1; Wu 2015).

Clear lakes were far more sensitive to dry vs. wet years than lower clarity, turbid lakes. Therefore, given current trends in precipitation, clear lakes may be the most sensitive indicators of effects of climate change on inland water bodies (Snucins and Gunn 2000). Beyond ecological effects, reduced water clarity also has both social and economic implications. For example, changes in water clarity are associated with perceptions of overall water quality (Heiskary and Walker 1988) and lakefront property values (Boyle et al. 1999, Gibbs et al. 2002). Clearer lakes are also more frequently visited and users are willing to travel further, bypassing less clear lakes, to spend time on high clarity lakes (Keeler et al. 2015). In addition to precipitation, extreme events are also increasing (Karl et al. 2009). While this study focused on interannual variations in precipitation, extreme events can rapidly reduce lake water clarity by flushing material into receiving water bodies. In some cases, large storms can reduce water clarity by >50% in hours to days (e.g., Rose et al. 2012).

Collectively, all predictors explained ~54–63% of variance among lake water clarity estimates, depending on whether it was a dry or wet year. What factors may contribute to the unexplained variance? First, uncertainty and variability in both predictor and response variables may be a substantial source. The accuracy of remotely sensed estimates of water clarity can vary with atmospheric conditions and quality of the citizen science data (see also, Appendix S1: Table S1). Additionally, while we used only summer samples, seasonal variability in water clarity may contribute noise. Second, unmeasured characteristics may be important regulators of water clarity. Our data set lacked many in-lake characteristic measurements, such as dissolved absorbance, algal biomass, and turbidity, which also regulate water clarity. While watershed features such as percent agriculture are correlated with algal biomass because they are sources of nutrients, other factors such as lake trophic structure also influence algal biomass, and consequently, water clarity (Sanderson 1998).

Latitudinal gradients in water clarity, land use/land cover, and the dominant factors regulating water clarity in lakes across Wisconsin may explain why percent wetlands was a top predictor of lake water clarity differences between the dry and wet years but did not explain spatial variability in clarity in either the dry or wet year. Lake water clarity in Northern Wisconsin (Ecoregion 50) is predominantly regulated by wetland-derived chromophoric dissolved organic matter (Gergel et al. 1999, Read and Rose 2013). Lake water clarity in Southern Wisconsin (Ecoregions 51, 52, and 53) is strongly driven by nutrient run-off from agricultural lands (Lathrop et al. 1999, Carpenter et al. 2007). As expected, there were more clear lakes in the north, but these clear lakes were vulnerable to degraded clarity during the wet year. Percent wetlands was the most important land use/land cover predictor of percent difference in clarity between the dry and wet years in the northerly Ecoregion 50, while wetlands were unimportant in the more southerly Ecoregions (51–53; see Appendix S1). These latitude and Ecoregion-specific results indicate that differences between the dry and wet year had larger effects on clarity in northern, DOC-regulated lakes than on southern, algal-regulated lakes. The responsiveness of DOC to precipitation is consistent with previous research (Schindler et al. 1996, Williamson et al. 2014). These results imply that lakes where water clarity is dominated by algal biomass (and not DOC) may be less responsive to interannual variations in precipitation.

Water clarity declined over time in nearly one-quarter of lakes. A recent analysis of citizen-collected water clarity records in 3251 lakes across eight states in the U.S. Midwest observed a smaller percentage of lakes (10.7%) were changing, with 6.9% increasing and 3.8% decreasing in clarity (Lottig et al. 2014). Similarly, using a 20-yr database (1985–2005) of remotely sensed observations of water clarity in >10000 lakes in Minnesota, Olmanson et al. (2013) detected trends in about 10.8% of lakes, but like our results, Olmanson et al. (2013) observed that more lakes were decreasing in clarity (6.2%) than were increasing (4.6%). Methodological differences and analysis time period are likely key factors contributing to different results among these studies. However, the substantial buildup of phosphorus in soils throughout the agriculturally dominated southern portions of Wisconsin (Bundy and Sturgul 2001) suggest that the decline may be real and continue for a long time.

The predictors of water clarity temporal trends highlight the importance of watershed features in regulating lake water clarity. Conductance, which was the only significant predictor of the direction of temporal trend, is controlled by features operating at the watershed or regional scale rather than lake-specific features (Brakke et al. 1988, Read et al. 2015). Meanwhile, the three characteristics that had significant interactions with antecedent precipitation (watershed wetlands, catchment to lake area ratio, and maximum depth) likely reflect the fact that wetlands are correlated with CDOM (and consequently water clarity in DOC-dominated lakes) and the catchment to lake area ratio may serve as a proxy for the degree of terrestrial inputs to lakes (Gergel et al. 1999, Winn et al. 2009, Solomon et al. 2013) or residence time. Clarity may have been insensitive to precipitation in lakes with high percent wetlands and/or high catchment to lake area ratios because these types of lakes are more likely to consistently exhibit high terrestrial-aquatic connectivity. Lakes with smaller catchment to lake area ratios may be less sensitive to precipitation because they have longer residence times. Deeper lakes (measured as maximum depth) were both more clear as well as more sensitive to precipitation, implying that any future changes in precipitation are likely to be most pronounced in deeper lakes.

The types of lake and watershed features that regulate water clarity constrain the management options available to maintain or improve lake water clarity. We found that many of the most important predictors of water clarity, such as lake depth, landscape position, and watershed slope, are features that cannot be readily managed. In lakes whose watersheds have little agriculture, variation in clarity is driven primarily by natural characteristics. In lakes with more than about 20% agriculture, particularly those that are shallow, the most effective way to improve water clarity appears to be limiting riparian agriculture (Fig. 5). This strategy will likely be even more important in the face of anticipated future increases in precipitation in the Great Lakes region.

It has been argued that lakes are sentinels of broader environmental change because they integrate changes occurring throughout their watersheds (Adrian et al. 2009, Williamson et al. 2009). Our results show that lake water clarity is responsive to a mixture of watershed and lake features, modulated by precipitation, implying that water clarity may serve as an ideal sentinel of both land cover/land use as well as climate and a useful management tool. These results build on studies demonstrating the important role of scale, hydrologic connectivity, and geographic region influencing how land use impacts lakes (Soranno et al. 2015). Understanding and managing trends in water clarity, and quality more broadly, represents an important challenge for water resource managers, especially in the face of mounting environmental changes. Fortunately, decades-long records of agency and citizen science collected water clarity records, in combination with remotely sensed records, provide an ideal mechanism to monitor water clarity patterns across space and time.

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Literature Cited

Adrian, R., et al. 2009. Lakes as sentinels of climate change. Limnology and Oceanography 54:2283–2297.

Allan, J. D. 2004. Landscapes and riverscapes: the influence of land use on stream ecosystems. Annual Review of Ecology Evolution and Systematics 35:257–284.

Allan, J. D., D. L. Erickson, and J. Fay. 1997. The influence of catchment land use on stream integrity across multiple spatial scales. Freshwater Biology 37:149–161.

Archer, K. J., and R. V. Kimes. 2008. Empirical characterization of random forest variable importance measures. Computational Statistics & Data Analysis 52:2249–2260.

Bates, D., M. Mächler, B. M. Bolker, and S. C. Walker. 2015. Fitting linear mixed-effects models using lme4. Journal of Statistical Software 67:1–48.

Boyle, K. J., P. J. Poor, and L. O. Taylor. 1999. Estimating the demand for protecting freshwater lakes from eutrophication. American Journal of Agricultural Economics 81: 1118–1122.

Brakke, D. F., D. H. Landers, and J. M. Eilers. 1988. Chemical and physical characteristics of lakes in the northeastern United States. Environmental Science and Technology 22:155–163.

Breiman, L. 2001. Random forests. Machine Learning 45:5–32.

Brenden, T. O., R. D. Clark, A. R. Cooper, P. W. Seelbach, L. Wang, S. S. Aichele, E. G. Bissell, and J. S. Stewart. 2006. A GIS framework for collecting, managing, and analyzing multiscale landscape variables across large regions for river conservation and management. Pages 49–74 *in* R. M. Hughes, L. Wang, and P. W. Seelbach, editors. American Fisheries Society Symposium. Volume 48.

Brezonik, P. L., L. G. Olmanson, M. E. Bauer, and S. M. Kloiber. 2007. Measuring water clarity and quality in Minnesota lakes and rivers: a census-based approach using remote-sensing techniques. Cura Report 37:3–13.

Bronstert, A., D. Niehoff, and G. Brger. 2002. Effects of climate and land-use change on storm runoff generation: present knowledge and modelling capabilities. Hydrological Processes 16:509–529.

Bundy, L. G., and S. J. Sturgul. 2001. A phosphorus budget for Wisconsin cropland. Journal of Soil and Water Conservation 56:243–249.

Carpenter, S. R., et al. 2007. Understanding regional change: a comparison of two lake districts. BioScience 57:323–335.

Chipman, J. W., T. M. Lillesand, J. E. Schmaltz, J. E. Leale, and M. J. Nordheim. 2004. Mapping lake water clarity with Landsat images in Wisconsin, U.S.A. Canadian Journal of Remote Sensing 30(1):1–7.

Correll, D. L. 1996. Buffer zones and water quality protection: general principles. Pages 7–20 *in* Buffer zones: their processes and potential in water protection. The proceedings of the international conference on buffer zones. Quest Environmental, Hertfordshire, UK.

Courville, B. C., J. L. R. Jensen, R. W. Dixon, and M. A. Fonstad. 2014. A Landsat-based evaluation of lake water clarity in Maine lakes. Physical Geography 35:355–368.

Cronshey, R. 1986. Urban hydrology for small watersheds. US Department of Agriculture, Soil Conservation Service, Engineering Division.

Curtis, J. T. 1956. The modification of mid-latitude grasslands and forests by man. Man's role in changing the face of the earth. University of Chicago Press, Chicago, Illinois, USA, 721–736.

Cutler, D. R., T. C. Edwards, K. H. Beard, A. Cutler, K. T. Hess, J. Gibson, and J. J. Lawler. 2007. Random forests for classification in ecology. Ecology 88:2783–2792.

Debano, L. F., and L. J. Schmidt. 1990. Potential for enhancing riparian habitats in the southwestern United States with watershed practices. Forest Ecology and Management 33–34:385–403.

Diebel, M. W., A. S. Ruesch, D. Menuz, J. Stewart, and S. M. Westenbroek. 2014. Ecological limits of hydrologic alteration in Wisconsin streams. Wisconsin Department of Natural Resources. http://digicoll.library.wisc.edu/cgi-bin/EcoNatRes/EcoNatRes-idx?id=EcoNatRes.DiebelHydrologic

Foster, D., F. Swanson, J. Aber, I. Burke, N. Brokaw, D. Tilman, and A. Knapp. 2003. The importance of land-use legacies to ecology and conservation. BioScience 53:77–88.

Fraterrigo, J. M., and J. A. Downing. 2008. The influence of land use on lake nutrients varies with watershed transport capacity. Ecosystems 11:1021–1034.

Fry, J., G. Xian, S. Jin, J. Dewitz, C. Homer, L. Yang, C. Barnes, N. Herold, and J. Wickham. 2011. Completion of the 2006 national land cover database for the conterminous United States. Photogrammetric Engineering and Remote Sensing 77:858–864.

Fuller, L. M., S. S. Aichele, and R. J. Minnerick. 2004. Predicting water quality by relating secchi-disk transparency and chlorophyll a measurements to satellite imagery for Michigan inland lakes, August 2002.

Gergel, S. E., M. G. Turner, and T. K. Kratz. 1999. Dissolved organic carbon as an indicator of the scale of watershed influence on lakes and rivers. Ecological Applications 9: 1377–1390.

Gibbs, J. P., J. M. Halstead, K. J. Boyle, and J.-C. Huang. 2002. An hedonic analysis of the effects of lake water clarity on New Hampshire lakefront properties. Agricultural and Resource Economics Review 31:39–46.

Heffernan, J. B., et al. 2014. Macrosystems ecology: understanding ecological patterns and processes at continental scales. Frontiers in Ecology and the Environment 12:5–14.

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

Hothorn, T., K. Hornik, and A. Zeileis. 2006. Unbiased recursive partitioning: a conditional inference framework. Journal of Computational and Graphical Statistics 15:651–674.

Information, N. N. C. for E. 2015. Climate monitoring: temperature, precipitation, and drought. Climatol. Rank.

Karl, T. R., J. M. Melillo, and T. C. Peterson. 2009. Global climate change impacts in the United States. T. R. Karl, J. M. Melillo, and T. C. Peterson, editors. Cambridge University Press, Cambridge, UK.

Keeler, B. L., S. A Wood, S. Polasky, C. Kling, C. T. Filstrup, and J. A Downing. 2015. Recreational demand for clean water: evidence from geotagged photographs by visitors to lakes. Frontiers in Ecology and the Environment 13: 76–81.

Kloiber, S. M., P. L. Brezonik, L. G. Olmanson, and M. E. Bauer. 2002. A procedure for regional lake water clarity assessment using Landsat multispectral data. Remote Sensing of Environment 82:38–47.

Kratz, T. K., K. E. Webster, C. J. Bowser, J. J. Magnuson, and B. J. Benson. 1997. The influence of landscape position on lakes in northern Wisconsin lakes. Freshwater Biology 37:209–217.

Lathrop, R. C., S. R. Carpenter, and D. M. Robertson. 1999. Summer water clarity responses to phosphorus, Daphnia grazing, and internal mixing in Lake Mendota. Limnology and Oceanography 44:137–146.

Lee, S.-W., S.-J. Hwang, S.-B. Lee, H.-S. Hwang, and H.-C. Sung. 2009. Landscape ecological approach to the relationships of land use patterns in watersheds to water quality characteristics. Landscape and Urban Planning 92:80–89.

Liaw, A., and M. Wiener. 2002. Classification and regression by randomForest. R News 2:18–22.

Lillesand, T. M., W. L. Johnson, R. L. Deuell, O. M. Lindstrom, and D. E. Meisner. 1983. Use of Landsat data to predict the trophic state of Minnesota lakes. https://ntrs.nasa.gov/search.jsp?R=19830040214

Liu, X., X. Zhang, and M. Zhang. 2003. Major factors influencing the efficacy of vegetated buffers on sediment trapping: a review and analysis. Journal of Environmental Quality 37:1667–1674.

Lottig, N. R., T. Wagner, E. Norton Henry, K. Spence Cheruvelil, K. E. Webster, J. A. Downing, and C. A. Stow. 2014. Long-term citizen-collected data reveal geographical patterns and temporal trends in lake water clarity. PLoS ONE 9:155–165.

Martin, S. L., and P. A. Soranno. 2006. Lake landscape position: relationships to hydrologic connectivity and landscape features. Limnology and Oceanography 51:801–814.

McCullough, I. M., C. S. Loftin, and S. A. Sader. 2012. Combining lake and watershed characteristics with Landsat TM data for remote estimation of regional lake clarity. Remote Sensing of Environment 123:109–115.

McCullough, I. M., C. S. Loftin, and S. A. Sader. 2013. Landsat imagery reveals declining clarity of Maine's lakes during 1995–2010. Freshwater Science 32:741–752.

Moran, J. M., and E. J. Hopkins. 2002. Wisconsin's weather and climate. University of Wisconsin Press.

Morris, D. P., H. Zagarese, C. E. Williamson, E. G. Balseiro, B. R. Hargreaves, B. Modenutti, R. Moeller, and C. Queimalinos. 1995. The attenuation of solar UV radiation in lakes and the role of dissolved organic carbon. Limnology and Oceanography 40:1381–1391.

Muggeo, V. M. R. 2003. Estimating regression models with unknown break-points. Statistics in Medicine 22:3055–3071.

National Oceanic and Atmospheric Association (NOAA) National Centers for Environmental Information (NCEI) Climatological Rankings 2015. Climate Monitoring: Temperature, Precipitation, and Drought. Access online at: https://www.ncdc.noaa.gov/temp-and-precip/climatological-rankings/

Olmanson, L. G., M. E. Bauer, and P. L. Brezonik. 2008. A 20-year Landsat water clarity census of Minnesota's 10,000 lakes. Remote Sensing of Environment 112:4086–4097.

Olmanson, L. G., P. L. Brezonik, and M. E. Bauer. 2013. Geospatial and temporal analysis of a 20-year record of Landsat-based water clarity in Minnesota's 10,000 lakes. Journal of the American Water Resources Association 50:748–761.

Omernik, J. M., and A. L. Gallant. 1987. Ecoregions of the upper midwest states. Corvallis, Oregon: US Environmental Protection Agency.

Omernik, J. M., A. R. Abernathy, and L. M. Male. 1981. Stream nutrient levels and proximity of agricultural and forest land to streams: some relationships. Journal of Soil and Water Conservation 36:227–231.

Peckham, S. D., and T. M. Lillesand. 2006. Detection of spatial and temporal trends in Wisconsin lake water clarity using Landsat-derived estimates of secchi depth. Lake and Reservoir Management 22:331–341.

R Core Team. 2015. R: a language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. https://www.r-project.org/

Read, J. S., and K. C. Rose. 2013. Physical responses of small temperate lakes to variation in dissolved organic carbon concentrations. Limnology and Oceanography 58:921–931.

Read, E. K., et al. 2015. The importance of lake-specific characteristics for water quality across the continental United States. Ecological Applications 25:943–955.

Rose, K. C., C. E. Williamson, J. M. Fischer, S. J. Connelly, M. Olson, A. J. Tucker, and D. A. Noe. 2012. The role of ultraviolet radiation and fish in regulating the vertical distribution of Daphnia. Limnology and Oceanography 57:1867–1876.

Sanderson, B. L. 1998. Factors regulating water clarity in northern Wisconsin lakes. University of Wisconsin-Madison, Madison, Wisconsin, USA.

Scarpace, F. L., L. T. Fisher, and K. W. Holmquist. 1979. Landsat analysis of lake quality. https://ntrs.nasa.gov/search.jsp?R=19790051485

Schindler, D. W., S. E. Bayley, B. R. Parker, K. G. Beaty, D. R. Cruikshank, E. J. Fee, E. U. Schindler, and M. P. Stainton. 1996. The effects of climatic warming on the properties of boreal lakes and streams at the Experimental Lakes Area, northwestern Ontario. Limnology and Oceanography 41: 1004–1017.

Schlosser, I. J., and J. R. Karr. 1981. Riparian vegetation and channel morphology impact on spatial patterns of water quality in agricultural watersheds. Water Resources Bulletin 17:233–243.

Snucins, E., and J. Gunn. 2000. Interannual variation in the thermal structure of clear and colored lakes. Limnology and Oceanography 45:1639–1646.

Soil Survey Staff, Natural Resources Conservation Service, U. S. D. of A. 2015. Web soil survey. http://websoilsurvey.nrcs.usda.gov/

Solomon, C. T., et al. 2013. Ecosystem respiration: drivers of daily variability and background respiration in lakes around the globe. Limnology and Oceanography 58:849–866.

Sophocleous, M. 2002. Interactions between groundwater and surface water: the state of the science. Hydrogeology Journal 10:52–67.

Soranno, P. A., et al. 1999. Spatial variation among lakes within landscapes: ecological organization along lake chains. Ecosystems 2:395–410.

Soranno, P. A., K. S. Cheruvelil, T. Wagner, K. E. Webster, and M. T. Bremigan. 2015. Effects of land use on lake nutrients: the importance of scale, hydrologic connectivity, and region. PLoS ONE 10:e0135454.

Tabacchi, E., D. L. Correll, R. Hauer, G. Pinay, A. M. Planty-Tabacchi, and R. C. Wissmar. 1998. Development, maintenance and role of riparian vegetation in the river landscape. Freshwater Biology 40:497–516.

Tong, S. T. Y., and W. Chen. 2002. Modeling the relationship between land use and surface water quality. Journal of Environmental Management 66:377–393.

Townsend, C. R., and R. H. Riley. 1999. Assessment of river health: accounting for perturbation pathways in physical and ecological space. Freshwater Biology 41:393–405.

Webster, K. E., P. A. Soranno, S. B. Baines, T. K. Kratz, C. J. Bowser, P. J. Dillon, P. Campbell, E. J. Fee, and R. E. Hecky. 2000. Structuring features of lake districts: landscape controls on lake chemical responses to drought. Freshwater Biology 43:499–515.

Whitehead, P. G., R. L. Wilby, R. W. Battarbee, M. Kernan, and A. J. Wade. 2009. A review of the potential impacts of climate change on surface water quality. Hydrological Sciences 54:101–123.

Williamson, C. E., J. A. Brentrup, J. Zhang, W. H. Renwick, B. R. Hargreaves, L. B. Knoll, E. P. Overholt, and K. C. Rose. 2014. Lakes as sensors in the landscape: optical metrics as scalable sentinel responses to climate change. Limnology and Oceanography 59:840–850.

Williamson, C. E., J. E. Saros, W. F. Vincent, and J. P. Smol. 2009. Lakes and reservoirs as sentinels, integrators, and regulators of climate change. Limnology and Oceanography 54(6part2):2273–2282.

Winn, N., C. E. Williamson, R. Abbitt, K. Rose, W. Renwick, M. Henry, and J. Saros. 2009. Modeling dissolved organic carbon in subalpine and alpine lakes with GIS and remote sensing. Landscape Ecology 24:807–816.

Wu, S. 2015. Changing characteristics of precipitation for the contiguous United States. 677–692.

Supporting Information

Additional supporting information may be found in the online version of this article at http://onlinelibrary.wiley.com/doi/10.1002/eap.1471/full

Data Availability

Data associated with this paper are available in the Long Term Ecological Research Network. Data Portal: https://doi.org/10.6073/pasta/95436b34f01b03286d9db033871e697c