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Abstract A classification system is often used to reduce the number of different ecosystem types that governmental agencies are charged with monitoring and managing. We compare the ability of several different hydrogeomorphic (HGM)—based classifications to group lakes for water chemistry/clarity. We ask: (1) Which approach to lake classification is most successful at classifying lakes for similar water chemistry/clarity? (2) Which HGM features are most strongly related to the lake classes? and, (3) Can a single classification successfully classify lakes for all of the water chemistry/clarity variables examined? We use univariate and multivariate classification and regression tree (CART and MvCART) analysis of HGM features to classify alkalinity, water color, Secchi, total nitrogen, total phosphorus, and chlorophyll *a* from 151 minimally disturbed lakes in Michigan USA. We developed two MvCART models overall and two CART models for each water chemistry/clarity variable, in each case comparing: local HGM characteristics alone and local HGM characteristics combined with regionalizations and landscape position. The combined CART models had the highest strength of evidence (ω_i range 0.92–1.00) and maximized within class homogeneity (ICC range 36–66%) for all water chemistry/clarity variables except water color and chlorophyll *a*. Because the most successful single classification was on average 20% less successful in classifying other water chemistry/clarity variables, we found that no single classification captures variability for all lake responses tested. Therefore, we suggest that the most successful classification (1) is specific to individual response variables, and (2) incorporates information from multiple spatial scales (regionalization and local HGM variables).

Keywords Ecoregion · Regionalization · Biogeochemistry · Water chemistry · Water clarity · Reference conditions · Eutrophication

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Introduction

Ecosystem structure and function are controlled in large part by the hydrology, geology, land cover, and climate characteristics of that ecosystem. These landscape features have been used to identify similarities in temperate (Host and others 1996) and tropical (Mora and Iverson 2002) forests, rangelands (Kunst and others 2005), streams (Frissell and others 1986) and their riparian zones (Vidon and Hill 2004), wetlands (Brinson 1993), lakes (Winter 1977; Riera and others 2000), and coral reefs (Rodgers 2005). For example, Brinson (1993) outlined an approach to wetland classification based on hydrologic and geomorphic features such as precipitation, groundwater flow, and landscape position. This hydrogeomorphic (HGM) approach was intended to provide a flexible classification framework based on knowledge of how HGM factors drive wetland structure and function. The accumulation of HGM data and the advancement of analytical techniques capable of handling complex datasets have extended the capacity of the HGM approach, making it possible to include more characteristics in the ecological classification of more ecosystem types (Host and others 1996).

Researchers have been classifying lakes since the early 1900s; in fact, lake classification was the major focus of the International Congress for Limnology in 1956 (Moss and others 1994), and interest in this topic has continued to the present, largely for the purpose of facilitating management. Agencies charged with lake management often desire a single comprehensive classification model within which individual lakes can be easily assigned to a group. These lake groups can then be used to help: (1) detect trends in water chemistry over time by accounting for variation among lake classes, (2) simplify management by grouping lakes where similar management strategies are likely to have similar results, and (3) set reference conditions.

Although a wide variety of approaches to classification has been adopted, one feature common to many has been to classify lakes based on the statistical similarity of water chemistry variables. Such a classification approach has been applied to lake water chemistry data in Canada (Pitblado and others 1980; Zimmerman and others 1983), Northeastern U.S. (Young and Stoddard 1996; Momen and Zehr 1998; and Jenerette and others 2002) and Sweden (Hakanson 1996; Hakanson 2005). However, these studies have not controlled for human impacts on water chemistry. As such, a change in human uses may result in a rapid change in the chemical composition of the lake, and thus, change the classification accuracy. It would be useful to create a classification using features that change little and are minimally impacted by human activities, such as HGM features. Such an HGM-based classification could then be used as the foundation upon which to evaluate the effect of human impacts, such as changes in land use or an introduction of exotic species. Therefore, knowing the role that HGM features play in driving variation among lakes is foundational to understanding the response of lakes to human impacts. Additionally, because HGM-based classifications are created using widely available geospatial data, they can be effectively applied to unsampled lakes without logistically challenging and expensive field collections. Thus, HGM-based classifications can be used for many more lakes than can be physically sampled (Brinson 1993; Young and Stoddard 1996), thereby allowing inferences and predictions to be made for individual lakes across broad geographic regions.

Regional land classifications (i.e., regionalizations) take advantage of the wealth of HGM data to group large geographic regions based on the similarity of physiographic, climatic and terrestrial features (Omernik 1987; Bailey and others 1994; Albert 1995). Interestingly, unlike these land classifications, few classifications of freshwater systems have taken an HGM approach. One hydrologically driven example of regionalization is the USGS hydrologic units (HUC; ***Seaber and others 1987). HUCs are delineated using topographical boundaries specific to a surface drainage area and have been used as management units by many agencies. More recent examples of HGM-based hydrological regionalizations include hydrologic landscape regions (HLR: Winter 2001; Wolock and others 2004) and ecological drainage units (EDU: Higgins and others 2005). The concept of hydrologic landscapes provides an aquatic analog to the land-based regionalization approaches, delineating land areas with similar HGM-drivers of surface and ground water movement and storage, specifically land-surface form, geologic texture, and climatic setting (Winter 2001; Wolock and others 2004). Alternatively, Higgins and others (2005) delineated EDUs by combining HUC watersheds with similar climate and landscape features. Although these regionalizations are conceptually appealing, the few studies testing such regionally-based lake classifications report that some critical lake water characteristics, such as nutrients and water clarity, are not always similar among lakes within these regions (Jenerette and others 2002; Cheruvelil and others 2008).

The concept of lake landscape position describes the local hydrologic landscape of a lake. Lake landscape position quantifies the hydrologic connectivity and spatial arrangement of various freshwater systems to infer similarity in ground and surface water hydrology (Kratz and others 1997; Martin and Soranno 2006). Several metrics of landscape position have been derived measuring various combinations of local hydrologic connectivity to other freshwater ecosystems (e.g., streams, lakes, wetlands). Each of these metrics of landscape position has shown significant relationships with important lake ecosystem characteristics, such as acid neutralizing capacity, dissolved organic carbon and nitrogen to phosphorus ratio (Kratz and others 1997; Martin and Soranno 2006). However, water clarity and productivity measures have not shown significant relationships with landscape position metrics (Riera and others 2000; Quinlan and others 2003; Martin and Soranno 2006).

Although many of the above ecological classification schemes have demonstrated some success in classifying lakes, they do so with little regard to other important HGM features and leave much variation to be explained. For example, although some regionalizations successfully group lakes with similar water quality, mechanisms that act through local-scale variables, such as lake morphometry, are not incorporated into such regionalizations and are likely important for lake classification success (Cheruvelil and others 2008). Conversely, some classification efforts have focused on only local-scale HGM features, ignoring variation captured in the larger scale metrics. More recently, there has been an emphasis on including both regional and local scale variables simultaneously in analyses of stream and lake characteristics (Seelbach and others 1997; Goransson and others 2004; Stendera and Johnson 2006) and calls for an approach that combines regional and local features (Pyne and others 2007; Cheruvelil and others 2008).

A combined approach, however, has inherent technical demands; it must be able to incorporate both continuous and categorical data, and account for local scale variation concurrently with regional scale phenomena. To date, the majority of statistical techniques that have been employed for classification development have used traditional linear models, such as principal components analysis and clustering (Bryan 2006). Classifications created with these linear methods are limited statistically when including categorical variables, such as regionalization or landscape position. By including such spatially-explicit categories into a larger classification framework, additional variation in water characteristics may be captured that local HGM data alone may miss. In addition, although linear approaches have been found to accurately represent some ecological relationships, these approaches may not effectively represent non-linear relationships and may mask the true character of the data by forcing it to conform to a linear arrangement (De'Ath and Fabricius 2000; Robertson and others 2006; Soranno and others 2008).

To date, few classification efforts have taken advantage of advances in statistical methods that alleviate some of the above mentioned shortcomings (but see Emmons and others 1999; Olden and Jackson 2002; Robertson and others 2006). Classification and regression tree (CART) analysis is a non-linear recursive partitioning approach capable of simultaneously including categorical and continuous variables (De'ath and Fabricius 2000; De'ath 2002). Groups created from a CART analysis have multiple uses in a management framework, such as to approximate reference conditions or to define groups of lakes that have similar HGM settings. Lakes with similar HGM characteristics are likely to respond similarly to environmental stressors and changes, such as increases in nutrient input from land use changes in the watershed.

The goal of our study is to develop and test several possible classifications for lake water chemistry/clarity that incorporate HGM features over multiple spatial scales. More specifically, management agencies often apply similar regulations and/or treatments to lakes within each lake group. Therefore, in addition to comparing among multiple univariate classifications, we also investigate the effectiveness of creating a single classification for all water chemistry/clarity variables using multivariate classification and regression tree analysis. We incorporate the broad-scale patterns captured by regional summaries of HGM features (i.e., regionalizations) in addition to local HGM features that are intrinsic to each lake (e.g., lake morphometry). We strive to create a lake classification that: (a) maximizes within-class homogeneity and between-class heterogeneity for lake water chemistry/clarity, (b) is based on HGM features that are temporally stable on the scale of decades to centuries, (c) minimizes the confounding effects of anthropogenic landscape features (e.g., human disturbances such as land use/cover), and (d) provides an example of a broadly applicable classification approach for other freshwater ecosystems. We ask three questions: (1) Which HGM-based approach to lake classification is most successful at grouping lakes with similar water chemistry/clarity (regionalization, landscape position, HGM features, or some combination)? (2) Which HGM features are most strongly related to the lake classes? and (3) Can a single lake classification successfully group lakes for all of the water chemistry characteristics examined? Answers to these questions can most directly benefit the management of lakes but can also be used to advance our understanding of how HGM features create a template upon which other drivers of ecosystem variation, such as human disturbance, are superimposed.

Methods

Our dataset includes 151 minimally disturbed lakes in Michigan, U.S.A. that are greater than 20 hectares in area. We define minimally disturbed lakes as those with no dam or water control structure and less than 25% human land use/cover (i.e., agriculture and urban) in the cumulative catchment (defined below). Our study lakes had only an average of 8% human land use/cover in the cumulative catchment and were surrounded mostly by forest (mean 80% forested land use/cover). We chose to limit our dataset to these lakes in order to reduce the confounding effects of human disturbances and maximize our ability to detect relationships with HGM characteristics (D'arcy and Carignan 1997; Stoddard and others 2006).

We obtained data on lake water chemistry/clarity during the time period of 1975 through 1982 from the U.S. EPA Storet database. The Michigan Department of Environmental Quality sampled the epilimnion of each lake during summer stratification (July, August, and September) for a wide range of limnological variables: alkalinity, water color, Secchi disk depth, total nitrogen (TN), total phosphorus (TP), and chlorophyll *a* (Chl *a*). The study lakes vary widely in all variables (Table 1).

Hydrogeomorphic Characteristics

Similarly to Brinson (1993), we define HGM characteristics as those linked to the geology, hydrology and

Table 1 Summary of lake water chemistry/clarity and hydrogeomorphic characteristics for 151 minimally disturbed lakes in Michigan USA

	Units	Min.	Max.	Mean	SD
Water chemistry/clarity					
Alkalinity	mg/L	1	206	72	55
Water color	PCU	1	99	14	16
Secchi	m	0.8	7.9	3.4	1.3
Total nitrogen (TN)	μg/L	88	1044	461	192
Total phosphorus (TP)	μg/L	1.0	32.0	11.7	6.0
Chlorophyll *a* (Chl *a*)	μg/L	0.2	29.0	4.3	4.4
Bedrock geology					
Carbonate (B-Carb)	%	0.0	100.0	12.5	32.3
Clastic (B-Clast)	%	0.0	100.0	48.3	48.4
Hardrock (B-Hard)	%	0.0	100.0	20.5	38.5
Iron (B-Iron)	%	0.0	100.0	18.7	37.1
Surficial geology					
Bedrock (S-Bed)	%	0.0	100.0	3.2	16.9
Dune (S-Dune)	%	0.0	37.5	0.9	4.9
Glacial till (S-Till)	%	0.0	100.0	17.6	32.8
Lacustrine (S-Lacu)	%	0.0	100.0	9.8	27.4
Moraine (S-Mora)	%	0.0	100.0	27.7	41.2
Outwash (S-Outw)	%	0.0	100.0	36.0	42.5
Peat and muck (S-PeMu)	%	0.0	36.4	0.6	3.9
Lake morphometry					
Lake Area (LK)	km^2	0.20	70.38	2.84	9.34
Shape	unitless	1.1	6.3	1.9	0.7
Mean depth	m	1.2	21.8	4.9	3.3
Maximum depth (Max. Depth)	m	3.0	58.5	14.4	9.2
Water residence time (WRT)	year	1.2*	31.6	2.5	4.2
Local catchment morphometry (LOCA)					
Area	km^2	0.2	1759.3	52.0	182.0
Shape	unitless	1.1	3.0	1.7	0.3
Slope	%	0.6	4.9	2.4	1.0
Cumulative catchment morphometry (CUCA)					
Area	km^2	0.2	1948.3	86.0	276.7
Shape	unitless	0.0	2.6	0.6	0.4
Slope	%	0.6	5.7	2.8	1.1
CUCA:LK	ratio	0.9	2655.1	63.5	247.1
CUCA:LOCA	ratio	1.0	14.4	1.6	2.2
Climate/hydrology					
Precipitation	cm/year	72.7	90.8	81.7	4.1
Runoff	cm/year	20.3	50.8	35.8	5.5
Baseflow index (BFI)	%	55	89	71	9
Wetlands					
CUCA	%	0	25	5	5
LOCA	%	0	23	4	4
500 m buffer	%	0	40	7	7
100 m buffer	%	0	53	8	11

Variables are arranged into broad categories. *Asterisk* is used to indicate a change in units for minimum WRT to days. *Abbreviations* are listed in *parentheses*. *PCU* platinum cobalt units. *CA:LK* catchment area to lake area ratio, *CUCA* cumulative catchment area, *LOCA* local catchment area

landscape context of a study ecosystem. With technological advancements in remote sensing and coordinated data collection strategies, large stores of HGM data are readily available in geographic information systems (GIS) for many areas of the world (Johnson and Gage 1997). We gathered geospatial data from multiple sources to create a digital HGM database for our study lakes. This database includes data about bedrock geology, surficial geology, lake morphometry, catchment characteristics, climate/hydrology, and wetland land use/cover. Geology and climate/hydrology were summarized within a 500 m buffer around each study lake. Wetlands were summarized over four spatial scales: cumulative catchment, local catchment, 500 m buffer, and 100 m buffer.

Bedrock geology data were obtained from the Geologic Survey Division of the Michigan Department of Environmental Quality. Sedimentary clastic is the dominant bedrock type in Michigan and for many of our study lakes, but our dataset also includes lakes dominated by other bedrock types (Table 1). Surficial geology data were provided by the Michigan Natural Features Inventory and Michigan Department of Natural Resources. Outwash and moraine surficial geology types dominate the study lakes (Table 1).

Lake area, perimeter, shape, mean depth, and maximum depth were gathered from the bathymetric maps provided through the Michigan Department of Natural Resources. Mean depth was calculated by taking the average depth of approximately 100 points evenly spaced across each bathymetric map (Omernik and Kinney 1983). Lake shape was calculated as the ratio of shoreline perimeter to the circumference of a circle of the same area (Wetzel and Likens 2000). Water residence time (WRT) was estimated as: [(lake area*mean depth) ÷ (cumulative catchment area*runoff)]. Area, shape and slope were measured for both local and cumulative catchment.

Cumulative lake catchments (CUCA) were delineated to include the catchment area associated with all lakes and streams draining into the lake using 1:100,000 resolution stream hydrography data, digital elevation models (30 m resolution) and topographic maps. Using the above data, we also delineated local catchments (LOCA) as the portion of the cumulative catchment downstream from any upstream lake greater than 0.2 km^2.

Average annual precipitation for the period 1971–2000 was obtained from the Spatial Climate Analysis Service (www.ocs.oregonstate.edu). Average annual runoff for the period 1951–1980 (http://water.usgs.gov/GIS/metadata/usgswrd/XML/ofr96395_run.xml) and mean base-flow index (BFI: http://water.usgs.gov/GIS/metadata/usgswrd/XML/bfi48grd.xml) were obtained from USGS. These data were summarized within the 500 m buffer and are therefore an indication of the local scale inputs (***Gebert and others 1987). In using both of these datasets, we assume that runoff and baseflow values for inflowing streams near to lakes will be similar, and that these data provide a way to compare relative amounts of runoff and baseflow across the lakes in our dataset rather than actual values of runoff or baseflow.

Wetland land use/cover data (30 m resolution) were obtained from the Michigan Resource Information Service (http://www.ciesin.org/datasets/mirislcover/miriscov.html) based on aerial photo interpretation of photos taken between 1978 and 1985.

Existing HGM-Based Classifications

We included three regionalization frameworks: (1) USGS 8-digit hydrologic units (HUC: Seaber 1987), (2) ecological drainage units (EDU: Higgins and others 2005), and (3) hydrologic landscape regions (HLR: Winter 2001). The location of each study lake within each region determined the class membership. Our study lakes were located within 19 HUCs, 6 EDUs, and 5 HLRs (Fig. 1).

We included three metrics of landscape position that can be easily measured from existing data using GIS (described in brief here, see Martin and Soranno (2006) for more detailed descriptions). Lake hydrology (LH) is a general measure of lake surface hydrologic connections, incorporating both connections to streams and lakes. Our analysis included lakes with LH categories of "S" seepage (lake has no surface inlet or outlet), "I" inflow (lake has surface inflow only), "IO" inflow-outflow (lake has both surface inlet and outlet but no lake connections), "H" headwater (lake has no surface inlet but does have outlet with downstream lake connections), "IH" inflow headwater (lake has surface inlet with no upstream lake connections but does have downstream lake connections), "F" flow-through (lake has upstream and downstream surface connections to lakes), and "T" terminal (lake only has upstream lake connections but has outlet). Lake network number (LNN) measures the degree of surface connectivity to other lakes by counting the number of upstream lakes. Our analysis included lakes with LNN categories of "0" zero, one "1", two "2", three "3" or greater than or equal to four "4+". Lake network complexity (LNC) is a measure of the complexity of connections to other lakes (e.g., dendritic or linear chain). Our analysis included lakes unconnected to any other lakes, indicated by LNC categories for no stream connection "-" and for only stream connection "OS", as well as lakes connected to other lakes through a linear chain "LS" or through a dendritic network "+".

Development of New Classifications

We developed and tested four new HGM-based classifications for each lake water chemistry/clarity variable using: (1) local HGM features for each study lake (HGM) only, and (2) local HGM features combined with existing HGM-based classifications: regionalizations and landscape position (HGM+). These classifications were created using

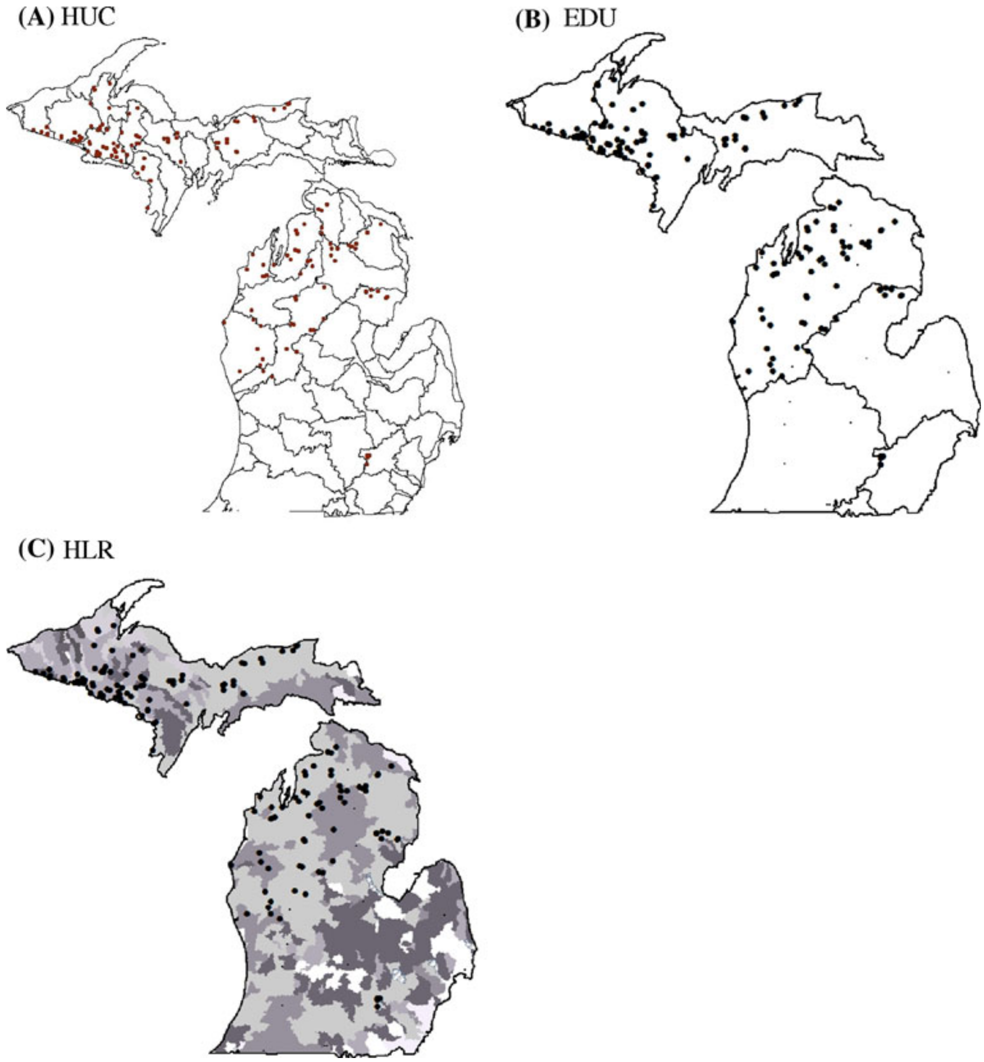

Fig. 1 Map of the upper and lower peninsula of Michigan, USA. Lakes included in the analysis are shown as solid dots. Boundaries are shown for each regionalization: **a** 8-digit USGS hydrologic units (HUC), **b** ecological drainage units (EDU), and **c** hydrological landscape regions (HLR)

two approaches: (1) classification and regression tree (CART) analysis, and (2) multivariate classification and regression tree (MvCART) analysis. In both tree-based approaches, all HGM variables enter as potential splitting variables. However, in the CART analysis, each individual water chemistry/clarity variable is used separately as the response whereas in the MvCART all water chemistry/clarity variables are used simultaneously as the response.

We chose to use tree-based models because they: (1) maximize class homogeneity, (2) do not penalize for including many independent variables, (3) handle high-order interactions among variables, and (4) accommodate both continuous and categorical data (De'ath and Fabricius 2000; De'ath 2002). All CART models were built using the recursive partitioning algorithm "rpart" in the R software system (R Development Core Team, http://www.R-project.org). All MvCART models were built using the multivariate recursive partitioning algorithm "mvpart" in the R software system (R Development Core Team, http://www.R-project.org). Both CART and MvCART trees were grown using 10-fold cross-validation and subsequently pruned using the 1-SE rule (Breiman and others 1984; Venables and Ripley 1999). Terminal nodes (i.e., lake classes) were required to have a minimum of five observations (i.e., lakes). The proportional reduction in error (PRE) for each split was summed to produce an overall PRE for each tree.

Output detailing splitting decisions from each tree was reviewed to assess tree stability and correlations among independent variables. Independent variables maximizing class homogeneity and PRE were always selected as the primary splitter. The top five independent variables for a primary split, measured by class homogeneity, were considered as competitors. The top five independent variables grouping lakes into classes similarly to the primary split, measured by percent agreement, were considered as surrogates (R Development Core Team, http://www.R-project.org). We assessed tree stability using information about competitor and surrogate splits, in combination. A split was considered (1) stable if there were no competitor splits within 3% reduction in error from the primary splitter, (2) somewhat stable/unstable if there were competitor splits within 3% reduction in error from the primary splitter but these competitors were also surrogates, or (3) unstable if there were competitor splits within 3% reduction in error from the primary splitter but these competitors were not surrogates. Therefore, given small changes in input data (1) stable trees are not likely to change in tree structure or class membership, (2) somewhat stable/unstable trees may split on different independent variables yet yield similar class membership, and (3) unstable trees would likely yield different tree structure and class membership.

Comparing Classifications

Two model selection statistics were used to compare among the candidate classifications for each lake water characteristic. First, we took an information-theoretic approach for multi-model comparison, using Akaike weights (ω_i) calculated from the corrected Akaike information criteria (AIC_C) for small sample sizes (Burnham and Anderson 2002), computed in SAS (SAS Institute Inc.). We compared the relative support for each classification using Akaike weights (ω_i). These weights sum to equal 1 and are interpreted as the probability that a model is the best model relative to others included in the analysis (Johnson and Omland 2004). Second, we used the intraclass correlation coefficient (ICC) to compare the ability of each of the classifications to maximize class homogeneity for each dependent variable (Donner and Koval 1980). This type of correlation has been widely used in social sciences and has more recently appeared in environmental sciences in terms of hierarchical linear models (Cheruvelil and others 2008). We calculated the ICC from the error terms of a one-way ANOVA with random effects:

$$Y_{ij} = \gamma_{00} + r_{ij} + u_{0j}$$

where, Y_{ij} = observation of dependent variable for lake i in lake group j, γ_{00} = grand mean of the dependent variable, r_{ij} = random error term for lake $_i$ in lake group $_j$, where $r_{ij} \sim N(0, \sigma^2)$ and σ^2 represents the within-group error in the dependent variable, u_{0j} = random error term for lake group j, where $u_{0j} \sim N(0, \tau_{00})$and τ_{00}represents the among-group error in the dependent variable. The ICC is the amount of the total variance that is among groups:

$$\text{ICC} = \hat{\tau}_{00} / \left(\hat{\tau}_{00} + \hat{\sigma}^2 \right)$$

A successful classification has a high ICC, meaning that a large amount of the variation is among the groups created from the classification, maximizing class homogeneity. All variables used in linear techniques (i.e., ANOVA) were transformed to meet normality assumptions.

We used the Akaike weights and the ICC to compare the success of each of the three regionalization frameworks (HUC, EDU, HLR), each of the three landscape position metrics (LH, LNN, LNC), our two CART models (HGM, HGM+), and our two MvCART models (HGM, HGM+) for classifying each of the six lake water characteristics included in this study (alkalinity, water color, Secchi, total nitrogen, total phosphorus, and chlorophyll *a*). We also used the PRE to compare among tree-based models.

To determine which HGM features were related to the lake classes, we further analyzed the splitting decisions of the tree-based models. We compared which HGM variables were chosen as primary, competitor, and surrogate splits in each CART model. We also analyzed the stability of each model using the detailed CART output.

We took two approaches to determine the success of using a single classification for all water chemistry/clarity variables: (1) an assessment of classification success of each of the two MvCART classifications (HGM and HGM+) when applied to each individual water chemistry/clarity variable, and (2) an assessment of classification success for each water chemistry/clarity variable when classified using CART models built for other water chemistry/clarity variables. First, although the MvCART models are parameterized for a multivariate combination of all six water chemistry/clarity variables, classification success (as measured by ICC values) is specific to each individual water chemistry/clarity variable. Thus, we calculated ICC values separately for each water chemistry/clarity variable using the HGM and HGM+ MvCART models, and compared the ability of these multivariately-derived models to build homogenous groups for each individual water chemistry/clarity variable. Second, we took a similar approach with the HGM and HGM+ CART models. Unlike the MvCART models, the CART models were parameterized independently for each lake water chemistry/clarity variable. Therefore, we could use the splitting rules from each response variable-specific CART to group lakes for each other response variable. For example, an HGM or an HGM+ CART model built specifically for alkalinity could be evaluated as a candidate classification model for each of the other lake water chemistry/clarity variables (i.e., water color, Secchi, TN, TP, and Chl *a*). The ICC could then be calculated and used to compare among all other models.

Results

Comparing Classifications

Classification success, indicated by class homogeneity and quantified by the ICC, ranged from 0% to 72% across all

Table 2 Summary of model selection statistics for candidate classifications per lake water characteristic

Lake water characteristic	Type	Name	ICC	K	AIC_C	ΔAIC_C	ω_i
Alkalinity	Regionalization	HUC	63	19	1545	38	0.00
		EDU	50	6	1586	79	0.00
		HLR	14	5	1626	119	0.00
	Landscape Pos.	LH	34	7	1598	91	0.00
		LNN	32	5	1609	102	0.00
		LNC	22	4	1617	110	0.00
	CART	HGM	56	4	1542	35	0.00
		HGM+	66	3	1515	8	0.02
	MvCART	HGM	57	4	1544	37	0.00
		HGM+	**72**	**5**	**1507**	**0**	**0.98**
Water color	Regionalization	HUC	17	19	404	43	0.00
		EDU	14	6	396	35	0.00
		HLR	15	5	403	42	0.00
	Landscape Pos.	LH	9	7	402	41	0.00
		LNN	4	5	409	48	0.00
		LNC	9	4	401	40	0.00
	CART	**HGM**	**46**	**4**	**361**	**0**	**0.92**
		HGM+	54	4	366	5	0.08
	MvCART	HGM	10	4	404	43	0.00
		HGM+	17	5	398	37	0.00
Secchi	Regionalization	HUC	0	19	522	68	0.00
		EDU	4	6	523	69	0.00
		HLR	0	5	524	70	0.00
	Landscape Pos.	LH	5	7	521	67	0.00
		LNN	2	5	524	70	0.00
		LNC	10	4	520	66	0.00
	CART	HGM	54	3	474	20	0.00
		HGM+	**50**	**5**	**454**	**0**	**1.00**
	MvCART	HGM	4	4	523	69	0.00
		HGM+	6	5	520	66	0.00
TN	Regionalization	HUC	13	19	182	57	0.00
		EDU	5	6	187	62	0.00
		HLR	0	5	185	60	0.00
	Landscape Pos.	LH	2	7	187	62	0.00
		LNN	0	5	185	60	0.00
		LNC	1	4	187	62	0.00
	CART	HGM	21	2	172	47	0.00
		HGM+	**47**	**6**	**125**	**0**	**1.00**
	MvCART	HGM	12	4	179	54	0.00
		HGM+	4	5	185	60	0.00
TP	Regionalization	HUC	13	19	291	46	0.00
		EDU	3	6	294	49	0.00
		HLR	2	5	295	50	0.00
	Landscape Pos.	LH	7	7	291	46	0.00
		LNN	0	5	293	48	0.00
		LNC	8	4	291	46	0.00
	CART	HGM	47	2	250	5	0.08
		HGM+	**39**	**3**	**245**	**0**	**0.92**

Table 2 continued

Lake water characteristic	Type	Name	ICC	K	AIC_C	ΔAIC_C	ω_i
	MvCART	HGM	3	4	294	49	0.00
		HGM+	13	5	285	40	0.00
Chlorophyll *a*	Regionalization	HUC	13	19	382	27	0.00
		EDU	9	6	378	23	0.00
		HLR	7	5	382	27	0.00
	Landscape Pos.	LH	1	7	386	31	0.00
		LNN	0	5	384	29	0.00
		LNC	1	4	386	31	0.00
	CART	**HGM**	**36**	**4**	**355**	**0**	**1.00**
		HGM+	n/a	n/a	n/a	n/a	n/a
	MvCART	HGM	1	4	386	31	0.00
		HGM+	9	5	381	26	0.00

Classification type is indicated as regionalization, landscape pos. (position), or CART. Individual classification names are indicated within each classification type. Intra-class correlation coefficients (ICC) are presented as percent of total variance that is among the classes. A high ICC indicates high within class homogeneity and thus, high classification success. The number of classes per classification model (K) is presented. ΔAIC_C is the difference between the AIC_C for each model and the minimum AIC_C for each lake water characteristic. The ΔAIC_C will equal 0 for the best model per lake water characteristic. The Akaike weights (ωi) sum to 1 for each lake water characteristic and is interpreted as the likelihood that a given model is the best model relative to others included in the analysis. n/a, not applicable

Classifications with the most support are indicated in bold font

classification approaches and all lake water chemistry/clarity variables (Table 2). Across lake water chemistry/clarity variables, alkalinity was classified most successfully (ICC mean 47%, range 14–72%), followed by water color (ICC mean 20%, range 4–54%). Secchi disk depth and measures of lake productivity were classified least successfully (ICC mean <12%) with 6 classification failures (ICC = 0%; Table 2).

For each lake water chemistry/clarity variable evaluated, we observed that one model received an Akaike weight greater than 0.9, and all other models received very low weights, less than 0.1 (Table 2). Thus, only one classification was supported by the data for each lake water chemistry/clarity variable, with supported models differing among the variables. No regionalization or metric of landscape position alone was supported as a suitable classification of any of our response variables, as AIC_C values were substantially higher than most CART models. Among all classification approaches and all lake water chemistry/clarity variables, with the exception of alkalinity, CART models had the highest strength of evidence (ω_i range 0.92–1.00) and were the most successful at maximizing within class homogeneity (ICC range 36–66%). Alkalinity was classified best when using the MvCART approach in combination with HGM+ predictors (Table 2). Among CART and MvCART approaches, HGM+ models had more AIC_C support than HGM models for a majority of lake water chemistry/clarity variables. Only two lake water chemistry/clarity variables (water color and Chl *a*) had a higher weight of evidence for HGM models. The HGM+ CART model for Chl *a* did not differ from the HGM CART model and, therefore, was not included in comparisons of model fit (indicated by "n/a" in Table 2).

Class homogeneity (ICC) was not always maximized by the most parsimonious model, as indicated by AIC_C (Table 2). According to weight of evidence, the best classification for water color, Secchi, and TP had ICC's 12%, 4%, and 8%, lower, respectively, than the maximum ICC for that lake water characteristic.

Relationships Between Hydrogeomorphic Features and Lake Classes

HGM CART models divided the study lakes into between 2 and 4 lake classes, capturing between 16% and 53% of the variation among lakes (PRE, Fig. 2). Measures of lake morphometry were the most frequent classifiers across HGM CART models (4 of 6 models). Mean depth, in particular, was the most important feature driving HGM CART models of lake productivity, with water residence time and maximum depth also included in some models. Various measures of catchment morphometry were important in classifying alkalinity and water color. The proportion of the local catchment in wetlands was the most important classifier for water color and Chl *a*. Geology and climate variables were present in only one model each (Chl *a* and alkalinity, respectively).

HGM+ CART models divided the study lakes into between 3 and 6 lake classes, capturing between 30% and 60% of the variation among lakes (Fig. 3). All

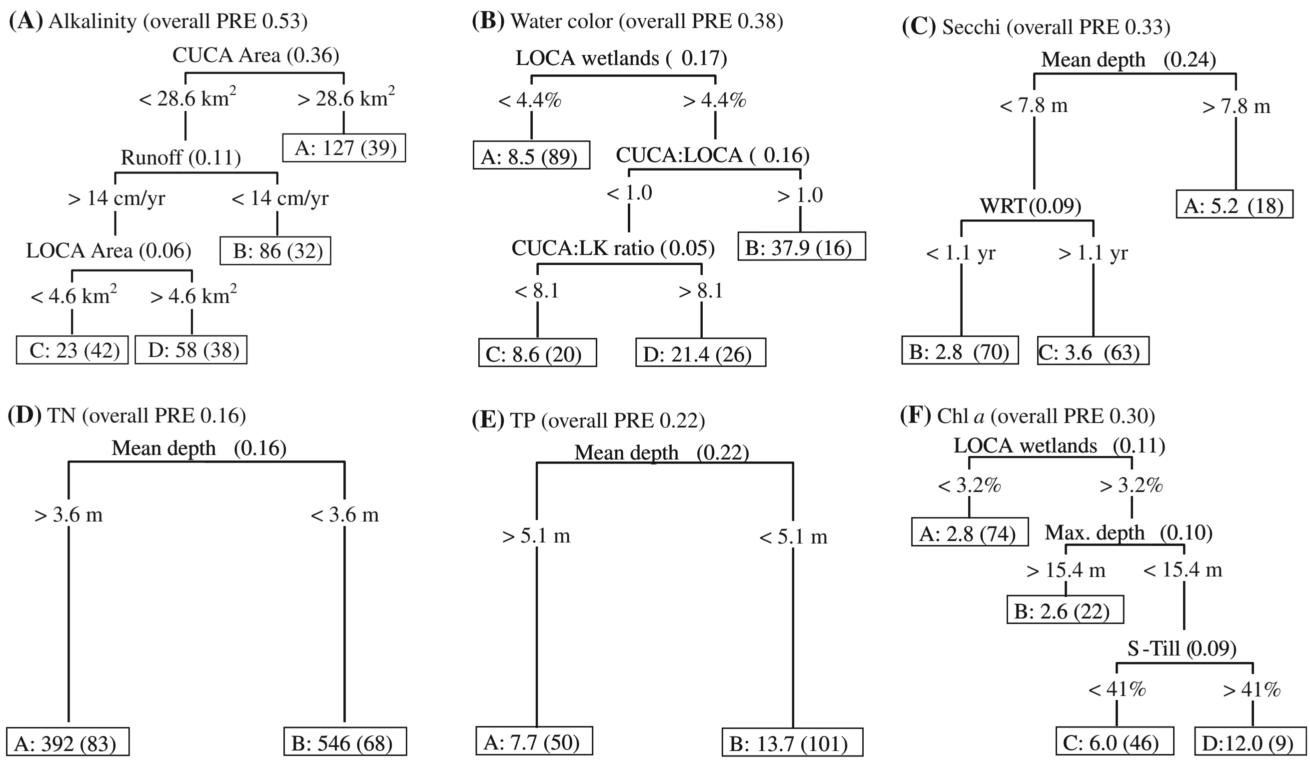

Fig. 2 Results from the CART analysis of local hydrogeomorphic features (HGM) for classifying lake water characteristics: **a** alkalinity, **b** water color, **c** Secchi, **d** TN, **e** TP, and **f** Chl *a*. Each split is labeled with the splitting variable (see Table 1 for *abbreviations*), and proportional reduction in error (PRE). Branches are labeled with splitting value. Terminal nodes (*rectangles*) represent lake classes and are labeled with an alphabetical class, class mean, and number of lakes per class (*in parentheses*)

HGM+ CART models (except Chl *a*) explained more variation than HGM CART models: alkalinity by 6%, water color by 11%, Secchi by 12%, TN by 30%, and TP by 8%. All HGM+ CART models (except Chl *a*) included the regionalization framework HUC as an important classifier (Figs. 2 and 3). No landscape position metrics were included as important classifiers in any of these models. As with HGM CART models, measures of lake morphometry were frequently important classifiers across HGM+ CART models (4 of 6 models), followed by catchment morphometry and wetlands (2 of 6 models each). The proportion of clastic bedrock geology type was present in the HGM+ CART model for TN. Climate was not included as an important splitting variable in any of the HGM+ CART models. The tree structure for most lake water chemistry/clarity variables was similar when comparing between HGM CART models and HGM+ CART models (Figs. 2 and 3). Most notably, the HGM+ CART model of Chl *a* did not include any regionalizations and was, therefore, identical to the HGM CART model. HGM CART and HGM+ CART models for Secchi and TP shared initial structure and classification variables, differing only by the addition of HUC as the last classifier. Alternatively, the HGM features driving the two CART classifications of water color were from the same broad categories; however, different variables represented these categories. More specifically, for the HGM CART model of water color, catchment morphometry was represented by both the ratio of cumulative catchment area to local catchment area (CUCA:LOCA) and the ratio of cumulative catchment area to lake area (CA:LK), whereas in the HGM+ CART model, catchment morphometry was represented by one variable (cumulative catchment shape, CUCA shape).

Despite these similarities, there were also some striking differences between HGM CART models and HGM+ CART models. For example, all HGM features included in the HGM CART model for alkalinity were completely replaced by regionalizations in the HGM+ CART model, with the 1st split (HUC) explaining 50% of the variation (Figs. 2 and 3). In another example, the tree structure for the HGM+ CART model for TN is quite different than the HGM CART model, although lake morphometry is still important for classifying TN in both models. Catchment morphometry and bedrock geology are additional HGM features included in the HGM+ CART model of TN, increasing the number of classes created from 2 in the HGM CART model to 6 in the HGM+ CART model.

MvCART models showed some similarities to the variable-specific CART models, most noticeably between

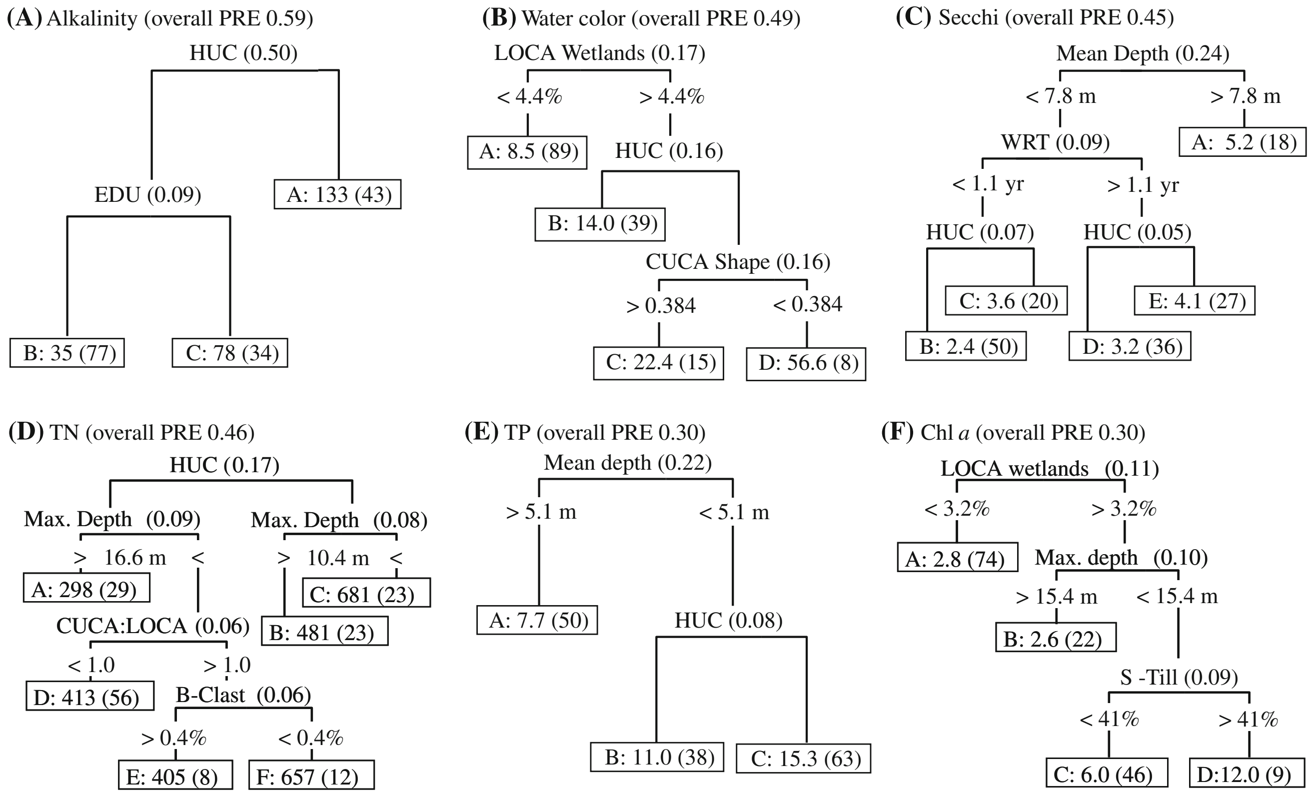

Fig. 3 Results from the CART analysis combining regionalization, landscape position and local hydrogeomorphic features (HGM+) in classifying lake water characteristics: **a** alkalinity, **b** water color, **c** Secchi, **d** TN, **e** TP, and **f** Chl *a*. Each split is labeled with the splitting variable (see Table 1 for *abbreviations*), and proportional reduction in error (PRE). Branches are labeled with splitting value. Terminal nodes (*rectangles*) represent lake classes and are labeled with an alphabetical class, class mean, and number of lake per class (*in parentheses*)

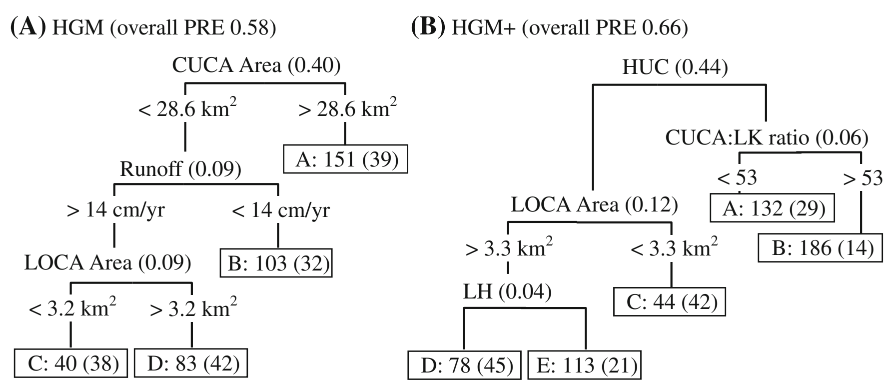

Fig. 4 Results from the MvCART analysis for classifying lake water characteristics using: **a** local hydrogeomorphic features (HGM), and **b** regionalization, landscape position and local hydrogeomorphic features (HGM+). Each split is labeled with the splitting variable (see Table 1 for *abbreviations*), and proportional reduction in error (PRE). Branches are labeled with splitting value. Terminal nodes (*rectangles*) represent lake classes and are labeled with an alphabetical class, class mean, and number of lake per class (*in parentheses*)

the >HGM MvCART and HGM CART for alkalinity (Figs. 2a, 4a). These two models are almost identical in splitting variables and values, as well as number of terminal nodes and observations per node. Only the last split differs in the splitting value for local catchment area (Figs. 2a, 4a).

Similarities between the HGM+ MvCART and the variable-specific CART models are less obvious but are present. HUC is the 1st split for the HGM+ MvCART as well as the alkalinity and TN HGM+ CART models (Figs. 3a, d, 4b). However, an analysis of the competitor and surrogate splits (data not shown) reveals cumulative catchment area as a surrogate for HUC in the HGM+ MvCART model, showing further similarities with the alkalinity HGM CART. Moreover, the cumulative catchment area splitting value is the same as the HGM MvCART and the alkalinity-specific HGM CART. Therefore, switching the 1st split in the HGM+ MvCART model from HUC to cumulative catchment area is likely to replicate the HGM MvCART model, which also mirrors the HGM CART model for alkalinity as detailed above. In summary, the HGM+ MvCART, HGM MvCART, and the HGM CART for alkalinity are all very similar in splitting decisions to one another. Therefore, because the MvCART models mimic the alkalinity-specific HGM CART in splitting decisions and receive no support from the Akaike weights for any water chemistry/clarity variables except alkalinity, we will not continue with further analysis of the MvCART models.

Evaluation of CART Tree Stability

Evaluating competitor and surrogate splitting options available in the detailed output from tree-based analyses can give a sense of the stability of a classification model. Some classification splits can be labeled as unstable (multiple competitors with none being surrogates, further detail in Methods), thereby indicating a sensitivity of the resulting classification to the particular observations used to build the classification. For example, HUC is the most important classifier in the HGM+ CART model for TN. However, two other variables explain approximately 3% less variation than HUC and do not serve as surrogates (data not shown). Using our methods, this split can be labeled "unstable" and highly dependant on the input data. In contrast, we label the 2nd split in the TN HGM+ CART model as "somewhat stable" because mean depth explained only slightly less variation ($\sim$2%) than maximum depth, the primary splitter at this node. In this case, however, mean depth acts as a surrogate for maximum depth since the majority (94%) of lakes would follow the same splitting path under either scenario. Therefore, this split is likely to be less dependent upon the specific dataset used in the analysis and can be considered stable. Over all 32 splits created in the CART models, 28% of splits were stable, 31% were somewhat stable/unstable, and 41% were unstable. These unstable splits are specific to our study lakes and details about these splits, such as splitting variable and splitting value, should be used with extreme caution.

A Single Classification for All Lake Water Chemistry/Clarity Variables

The power of MvCART is that it is capable of creating a single classification for all response variables. However, classification success will still vary across response variables. Our HGM and HGM+ MvCART models ranged in ICC from 72% to 1%, with all but alkalinity classified with low success (ICC < 13%; Table 2). Our results show that both MvCART models for alkalinity can be reduced down to the HGM CART model, and no other water chemistry/clarity variables were successfully classified by either MvCART model.

In addition to using MvCART to investigate a single classification for all water chemistry/clarity characteristics, we compared the classification success of variable-specific CART models for classifying other lake water chemistry/clarity variables. Table 3 is a matrix of ICC values from variable-specific HGM and HGM+ CART models (rows) when used to classify each water chemistry/clarity variable (columns). Therefore, classifying alkalinity using the alkalinity-HGM CART model has the same ICC value as reported in Table 2 (i.e., 56). In contrast, using the splitting rules from the alkalinity-HGM CART, but then comparing water color values among lakes yields an ICC of 7. Thus, the alkalinity-HGM CART model performs very poorly for grouping lakes with similar water color.

Table 3 also includes columns for the mean ICC across all water chemistry/clarity variables for each CART model and rank of the mean. The mean ICC across water chemistry/clarity variables for the Secchi-HGM CART model ranked highest at 38% (Table 3). Class homogeneity varied slightly for most lake water chemistry/clarity variables when classified by the Secchi-HGM CART model in comparison to the variable-specific CART models. Homogeneity increased for water color (1%), Secchi (4%), and Chl *a* (2%), and decreased only a moderate amount for TN (6%) and TP (8%). However, the class homogeneity decreased much more for alkalinity (50%). Simple correlations indicate that Secchi is significantly correlated to all lake water chemistry/clarity variables, except alkalinity (Table 4). Our results show that using the best overall variable-specific CART model to classify other water chemistry/clarity variables has reasonable success for those variables that are correlated but is not successful for non-correlated variables.

Although most lake water chemistry/clarity variables were significantly correlated with one another (Table 4), classification success varied widely when a single classification was used for all variables (Table 3). For example, alkalinity was significantly correlated with water color, TP, and Chl *a* (Table 4). However, neither of the alkalinity CART models successfully classified any other variable (mean ICC excluding alkalinity: HGM 6%, HGM+ 5%; Table 3). In another example, water color had the highest correlation with all lake water chemistry/clarity variables (except TP, Table 4), yet water color CART models ranked low for overall classification success (HGM rank 8, HGM+

Table 3 Summary of the intraclass correlation coefficients (ICCs) for CART models across lake water characteristics

CART model	Lake water characteristic						Mean	Rank
	Alkalinity	Water color	Secchi	TN	TP	Chl *a*		
Alkalinity-HGM	56	7	5	12	5	1	14	11
Alkalinity-HGM+	**66**	9	0	5	5	8	16	10
Water color-HGM	1	**46**	22	12	12	11	17	8
Water color-HGM+	22	54	50	7	9	11	26	5
Secchi-HGM	16	47	54	41	31	38	38	1
Secchi-HGM+	25	39	**50**	31	29	27	34	2
TN-HGM	5	14	19	21	26	12	16	9
TN-HGM+	22	38	36	**47**	40	12	33	3
TP-HGM	13	31	29	24	47	23	28	4
TP-HGM+	17	28	23	18	**39**	24	25	6
Chl *a*-HGM	6	31	19	15	20	**36**	21	7

CART models are listed by the original dependant variable and type of classification. Variable-specific classifications with most support (as shown in Table 2) are indicated in *bold* font. Mean ICC across lake water characteristics is computed. Rank of mean ICC is listed. See Table 2 for acronyms

Table 4 Pearson product-moment correlation coefficients for lake water chemistry/clarity

Lake water chemistry/clarity	Lake water chemistry/clarity					
	Alkalinity	Secchi	Water color	TN	TP	Chl *a*
Alkalinity	–					
Secchi	0.10^{NS}	–				
Water color	−0.22**	−0.66***	–			
TN	-0.02^{NS}	−0.45***	0.48***	–		
TP	−0.17*	−0.50***	0.53***	0.59***	–	
Chl *a*	−0.21**	−0.46***	0.52***	0.38***	0.39***	–

*** $P < 0.001$, ** $P < 0.01$, * $P < 0.05$, NS, not significant ($P > 0.05$)

rank 5; Table 3). Therefore, correlations among lake water chemistry/clarity variables did not predict classification success across all variables.

Discussion

There are three main conclusions that follow from our results. First, although some lake water chemistry/clarity variables were classified most successfully by local HGM features alone, most lake water chemistry/clarity variables were best classified when models included local HGM variables and one or more regionalization. This first conclusion highlights that water chemistry/clarity variables are influenced over multiple spatial scales. Second, lake and catchment morphometry plays a dominant role in structuring the classifications for the lake water chemistry/clarity variables. Third, creating a single classification for a wide range of response variables is not a straight-forward process and can severely erode the classification success for some water chemistry/clarity variables. Overall, because it is important for management agencies to balance the logistics and the effectiveness of classification, we suggest that the most successful classification system is (1) developed for a specific objective, such as watershed management, and (2) capable of incorporating information at multiple spatial scales and from a variety of different sources (regionalization and local HGM variables). We found that CART models effectively modeled the complex interrelationships among our explanatory variables and are thus a useful tool for the classification of lakes.

Comparing Classifications

Our results agree with previous studies showing that most lake water chemistry/clarity variables are not similar within many areas delineated by regionalizations (Jenerette and others 2002; Cheruvelil and others 2008). Regionalizations alone had poor classification success for all lake water chemistry/clarity variables, except alkalinity, which was classified well by HUCs and EDUs. Moreover, our alkalinity HGM CART model split on some characteristics that are more indicative of regional-scaled processes, such as climate. In another study of Michigan lakes, Martin and Soranno (2006) found strong relationships between landscape position and alkalinity. However, our results show that this relationship is comparatively weak in contrast to classifications based on broader-scale regionalizations. For example, landscape position (specifically, LH), explained 21% less variation than HUC in the 1st split of the alkalinity HGM+ model. These results may indicate that as the spatial scale of the classifying feature grows (LH $<$ HUC), the explanatory power for variation in alkalinity also grows (29% LH, 50% HUC). Therefore, while landscape position does account for some variation, alkalinity may be responding to phenomena that act over larger spatial scales, such as those captured by regionalizations (Griffith and others 1987; Cheruvelil and others 2008).

While regionalization alone is insufficient for effective classifications, using a combination of regional and local scale variables (i.e., HGM+) to classify lakes also performed better than the local only models (i.e., HGM). Overall, our results show that models incorporating multiple spatial scales (i.e., those combining regionalizations with local HGM features) successfully classified most lake water characteristics. However, in some cases, the addition of regionalizations did not change or even decreased classification success. For example, the HGM and HGM+ CART models for Chl *a* were the same (discussed below). In another example, although adding HUC to the model of water color increased the ICC by 8%, this increase in classification success was also accompanied by a decrease in model parsimony, as indicated by the Akaike weights. Thus, most but not all water chemistry/clarity variables are best modeled by HGM features measured over multiple spatial scales (i.e., HGM+ CART).

Our models of lake nutrient and water clarity variables seem to indicate a regional phenomenon not captured through local HGM characteristics. More specifically, the best classifications for Secchi, TN, and TP all included the HUC regionalization in addition to lake morphometry features. These results agree with previous findings suggesting that local HGM features, such as lake morphometry, are strong drivers of some lake productivity and water clarity variables (e.g., Vollenweider 1968; see Brett and Benjamin 2008 for a review). However, our results are novel in that they also show that most of these lake water characteristics respond to additional phenomena acting at larger spatial scales that are captured in regionalizations. Our results support the conjecture that a multi-scale classification system will be most successful for classifying lake water characteristics (Hakanson 2005; Stendera and Johnson 2006; Pyne and others 2007).

Relationships Between HGM Features and Lake Classes

HGM features important for splitting lake classes in CART models are similar to what we would expect based on previous studies on the relationships between lake water chemistry/clarity variables and lake morphometry (Fee 1979; Halsey and others 1997) and catchment morphometry (Wolock and others 1989; Rasmussen and others 1989; Hakanson 2005). Overall, we found that catchment features dominated the classification of alkalinity and water color whereas measures of lake morphometry were the most important classifiers of nutrients and Secchi.

Studies have previously reported that catchment morphometry is strongly related to lake productivity (D'arcy and Carignan 1997; Hakanson 2005); however, none of our classifications based solely on HGM features included any catchment morphometry features as 1st tier primary splits for productivity variables. One measure of catchment morphometry (CUCA:LOCA) was included as a 3rd tier primary split in the HGM+ CART model for TN. However, this variable explained little variation (6%), and was in competition with wetland presence at two spatial scales (data not shown). Moreover, catchment morphometry was not a strong competitor to split HGM CART models for nutrients (TN: no competitor with mean depth, TP: weak competitor explaining 15% less variation than mean depth). Inconsistencies among studies may be due in part to differences inherent in the underlying ecological relationships of the study regions. For example, our study lakes were ten times larger in surface area and spanned a wider range of mean depth, maximum depth, and water residence time than the lakes studied by D'arcy and Carginan (1997). Our study lakes were also larger and deeper with a longer WRT than the lakes studied by Hakanson (2005). Therefore, further study is required to more fully describe the relationship between catchment morphometry and lake productivity.

Wetland cover may be important for the dynamics of many lake water chemistry/clarity variables such as water clarity and productivity. In fact, previous studies report that wetlands act as a source of colored compounds (Detenbeck and others 1993; Halsey and others 1997; Prepas and others 2001). Our results show a positive relationship between wetlands and water color (Pearson r range 0.28 to 0.43 over all spatial scales, all P-values < 0.01), supporting these studies. Moreover, wetlands were the strongest classifier of water color in our study lakes, explaining more than WRT and groundwater input. These results suggest that water color in these minimally disturbed lakes may be more affected by source wetlands rather than by internal processing or by groundwater delivery, which contrasts with other studies (Rasmussen and others 1989; Hakanson 2005;

Webster and others 2008). We also found wetland land cover to be the strongest classifier of Chl *a*. The observed positive correlation ($r = 0.34$, P-value < 0.0001) between wetlands and Chl *a* may be an indirect result of a positive association between wetlands and TP ($r = 0.23$, P-value $<$ 0.01) and TN ($r = 0.24$, P-value < 0.01). Previous studies have shown that different wetland types (e.g., bog, fen) can play different roles in nutrient dynamics, with some serving as a source and others as a sink of phosphorus (Detenbeck and others 1993; Halsey and others 1997; Prepas and others 2001). Our results may indicate that our study lakes are responding to the confounding roles that wetlands can play in lake productivity, by both facilitating productivity through nutrient supply and by creating colored compounds that limit productivity through shading. However, finer-resolution data measuring the presence of different wetland types would be required to fully evaluate the role of wetlands in these lake dynamics.

It is also interesting to note that the water color and Chl *a* lake classes were split on a very small amount of wetlands (local catchment wetlands at 4% and 3%, respectively). One study reports that a much greater presence of wetlands in a catchment ($\sim$>50%) is needed before detecting significant relationships with water chemistry characteristics (Prepas and others 2001). However, other studies report much lower thresholds (6-25%) beyond which wetland presence becomes important (Dillon and others 1991; D'arcy and Carignan 1997; Canham and others 2004).

We also compared wetland cover measured over four spatial scales (cumulative catchment, local catchment, 500 m buffer, and 100 m buffer) and found that the proportion of wetlands in the local lake catchment was the only scale represented in any of the final CART classifications (water color and Chl *a*). However, analysis of tree stability shows that other spatial scales act as competitor and/or surrogate splits for all lake water water/chemistry variables (except alkalinity). In some cases, there were only small losses in explanatory power when choosing other spatial scales. For example, cumulative catchment wetland cover explained 2% and 0.5% less than local catchment wetland cover in the HGM models for water color and Chl *a*, respectively. Moreover, cumulative catchment wetland cover had 96% and 98% classification similarity with local catchment wetland cover. Although our results show that wetland presence at the local catchment scale is the strongest classifier for our study lakes, our results support other studies finding little difference in explanatory power between wetland cover measured at different spatial scales (Gergel and others 1999; Strayer and others 2003; Canham and others 2004). Therefore, additional investigations are needed to more fully understand the scale and magnitude of wetland presence that is important for lake ecosystem dynamics.

A Single Classification for All Lake Water Chemistry/Clarity Variables

Our results show that a lake classification model capable of successfully classifying lakes for all water chemistry/clarity variables likely does not exist. By comparing various multivariate and univariate classification approaches, we found that the most successful single classification for the lake water chemistry/clarity variables that we analyzed was Secchi HGM CART. As a measure of overall water clarity, Secchi can represent the expression of many water chemistry/clarity variables, such as nutrients, Chl *a*, DOC and turbidity. Therefore, it is appropriate that this integrated measure of water quality is also the most successful at classifying multiple water chemistry/clarity variables. However, using this single classification was on average 20% less successful in classifying other variables and as much as 50% less successful in classifying alkalinity. When compared to regionalizations, the Secchi HGM CART was on average 16% more successful in classifying chemistry/clarity variables and 29% better when alkalinity was excluded from the analysis. Thus, our results demonstrate that no single classification scheme can maximize success for all lake water chemistry/clarity variables because each classification depends on a different suite of local and regional HGM variables. Our results show that when limited to using a single classification model, overall classification success can be improved over using solely a regionalization scheme by choosing an integrated measure of ecosystem integrity, such as water clarity. Comparisons such as ours should help guide the application of different approaches to lake classification and allow for management agencies to make choices between logistical practicality and ecological robustness.

Applications to Ecosystem Management

A classification system is often used to reduce the number of different ecosystem types that governmental agencies are charged with monitoring and managing. To enhance the usefulness of any classification, we suggest that the creation of the classification follow a process that allows for the consideration of alternative classification models, specifically to include multiple measures of a characteristic over multiple spatial scales. Our use of detailed tree-based output allows for the evaluation of alternative splitting decisions which can then be used to allow for an assessment of practicality and/or cost to enter into the classification process. For example, our results show that susceptibility of lakes to acidification may be adequately captured at larger spatial scales, as lakes within regions had similar alkalinity, and thus is a cost-effective classification as these data are easy to collect for all lakes. On the other hand, management of nitrogen inputs to lakes should benefit from a more complex classification combining regionalizations and local HGM features, including lake maximum or mean depth. We recognize that information about lake depth is not available for all lakes, nor is it a variable that can be obtained from remote sensing at this time. However, this HGM feature does not change rapidly and, therefore, funds invested to collect lake morphometry data should be an excellent investment because of the data's longevity and importance for a large number of lake processes. For example, many Michigan lakes have bathymetric maps that date from 1929 through 1980. Our classification can be used to classify these lakes without an additional visit since lake morphometry features are stable over a relatively long time period in relation to water chemistry/clarity. In addition, maximum depth is less costly to measure than mean depth, and hopefully the use of new methods in remote sensing, such as radar, may aid in the collection of lake depth information for large numbers of lakes in the near future.

Our approach to lake classification combines the strengths of a regionalization approach and a local HGM-based approach with analytical advances in multivariate statistics. We recommend: (1) using HGM features measured over multiple spatial scales, (2) a tree-based approach to classification, with analysis of detailed splitting decisions, and (3) evaluating the cost of using a single classification for grouping disparate response variables. Our approach can fulfill the needs of management agencies for an ecologically-based classification system which will allow for robust trend detection through time by reducing variation in natural HGM features within each class, allowing for the proper focus to be placed on the identified stressors such as land use/change, climate change or change in public access and use of the resource. The classification of other ecosystem types such as streams and wetlands should also benefit from taking a multi-scale HGM-based approach by building upon foundational relationships between ecosystem function and hydrogeomorphic setting which can be measured over different spatial scales.

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