Journal of Great Lakes Research 39 (2013) 211–223

Contents lists available at SciVerse ScienceDirect

Journal of Great Lakes Research

journal homepage: www.elsevier.com/locate/jglr

Landscape-scale modeling of water quality in Lake Superior and Lake Michigan watersheds: How useful are forest-based indicators?

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ARTICLE INFO

Article history:
Received 23 March 2012
Accepted 8 March 2013
Available online 24 April 2013

Communicated by Edward Rutherford

Index words:
Forest disturbance
Water quality
Great Lakes
Landscape
Mixed effects model

ABSTRACT

The Great Lakes watersheds have an important influence on the water quality of the nearshore environment, therefore, watershed characteristics can be used to predict what will be observed in the streams. We used novel landscape information describing the forest cover change, along with forest census data and established land cover data to predict total phosphorus and turbidity in Great Lakes streams. In Lake Superior, we modeled increased phosphorus as a function of the increase in the proportion of persisting forest, forest disturbed during 2000–2009, and agricultural land, and we modeled increased turbidity as a function of the increase in the proportion of persisting forest, forest disturbed during 2000–2009, agricultural land, and urban land. In Lake Michigan, we modeled increased phosphorus as a function of ecoregion, decrease in the proportion of forest disturbed during 1984–1999 and watershed storage, and increase in the proportion of urban land, and we modeled increased turbidity as a function of ecoregion, increase in the proportion of forest disturbed during 2000–2009, and decrease in the proportion softwood forest. We used these relationships to identify priority areas for restoration in the Lake Superior basin in the southwestern watersheds, and in west central and southwest watersheds of the Lake Michigan basin. We then used the models to estimate water quality in watersheds without observed instream data to prioritize those areas for management. Prioritizing watersheds will aid effective management of the Great Lakes watershed and result in efficient use of restoration funds, which will lead to improved nearshore water quality.

Introduction

Water quality in lakes is profoundly influenced by the characteristics of the watersheds that support them (Allan et al., 1997; Arnold and Gibbons, 1996; Gergel et al., 2002). As the world's largest source of surface fresh water, the Laurentian Great Lakes are an important resource for the eight U.S. states and one Canadian province that border them. A recent analysis of data collected by the Bureau of Labor Statistics suggests that 1.5 million jobs are directly connected to the Great Lakes, and these jobs generate $62 billion in wages (Vaccaro and Read, 2011). In this study, we evaluate the relationship between landscape conditions, including novel forest predictors, in the watersheds of Lake Superior and Lake Michigan and water quality in streams draining those watersheds. These tributaries influence the water quality of the nearshore area of the Great Lakes, so our research will have an important application in the management of nearshore water quality for beneficial uses by fisheries and people. The nearshore region – defined as that portion of the lake directly influenced by contributing watersheds and extending from the shoreline to 20–30 m of depth (Edsall and Charlton, 1997; Mackey and Goforth, 2005) – is particularly important because it is used as a drinking water source, for recreation, and is an important aquatic ecosystem (Fuller and Shear, 1995).

The Great Lakes Restoration Initiative (GLRI) is a multi-million dollar investment to improve the health of Great Lakes watersheds by addressing toxic substances, invasive species, nearshore health and nonpoint source pollution, habitat and wildlife protection and restoration, and education, monitoring, evaluation, communication, and strategic partnership (WHCEQ, White House Council on Environmental Quality et al., 2010). In Fiscal Year 2010, 255 million dollars were awarded to 16 different federal agencies and 163 million dollars were awarded to other partners as grants (http://greatlakesrestoration.us/projects.html). In an era of shrinking resources, the Action Plan (WHCEQ, White House Council on Environmental Quality et al., 2010) identified the need for methods to target watersheds where management and restoration activities could be rapidly and effectively applied. Nonpoint source pollutants contribute to the degraded conditions in the Great Lake nearshore areas, but these sources can be challenging to pinpoint for restoration and management (Riseng et al., 2010). The Action Plan

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0380-1330/$ – see front matter. Published by Elsevier B.V. on behalf of International Association for Great Lakes Research.
http://dx.doi.org/10.1016/j.jglr.2013.03.012

identifies soluble reactive phosphorus, soil erosion, and pollutants as contaminants, so we developed models to predict and rank watersheds for two related variables, instream total phosphorus (TP) and turbidity (NTU [nephelometric turbidity units]).

There is a large literature describing the methods used to predict stream delivery of chemical and physical pollutants using watershed variables (e.g., land use, surficial geology). The methodologies used to model water condition in the Great Lakes have ranged from single watersheds (Bosch, 2008) to the entire U.S. basin (Robertson and Saad, 2011). There is a trade-off between the amount of time and data that are needed for a model and the spatial scale the model can describe. Mechanistic (or deterministic) models (e.g., Soil Water Assessment Tool (SWAT); Bosch, 2008) use complete, computational characterizations of watersheds (e.g., topography, hydrology, climate) to predict detailed nutrient and sediment exports. Mechanistic models are data intensive and would be difficult to parameterize for an entire Great Lake basin. A hybrid mechanistic–statistical method called SPAtially-Referenced Regression On Watershed attributes (SPARROW; Smith et al., 1997) uses a mass-balance approach that combines observed water quality and watershed features to model watershed export. This method can be used for larger spatial scales, and was recently completed for the Great Lakes (Robertson and Saad, 2011); it will provide a reference point for comparison with our models. We selected a statistical approach using landscape characteristics and observed water quality in multiple watersheds to create models that predict instream water quality (Lopez et al., 2008). Our method has the advantage of being effective for a large spatial area, while not having the intense data requirements of mechanistic models; it is also readily applicable to watersheds not already modeled using landscape characteristics alone, which is more difficult for other models, such as SPARROW. Our models also utilize higher resolution spatial data (30-meter pixels) compared to SPARROW, which uses county-level estimates of agricultural land use (Smith et al., 1997). Our models also utilize a newly available forest database that tracks the persistence and disturbance of forest through time. Forest has been closely linked to high quality water (de la Crétaz and Barten, 2007), especially in relation to intense human development, and forest also represents a wide range of potential restoration activities (e.g. tree planting, riparian buffer restoration). We developed models that can be used to address water clarity issues (NTU), in addition to nutrients (TP), so they can be used in association with the SPARROW models to link water quality with watershed and forest conditions.

The goal of this research is to provide the U.S. Environmental Protection Agency (USEPA) and watershed managers with models to predict water quality in gauged basins to predict future changes in water quality associated with landscape changes in the watersheds, and to prioritize the ungauged watersheds of Lake Superior and Lake Michigan for restoration. We will link the landscape characteristics in each basin to observed water quality in streams that contribute to nearshore water quality. The models will then be applied to ungauged sites to identify areas with watershed conditions that may lead to degraded water quality. Ranked watershed groups can then be used to target the areas in the basin where management is most needed and where restoration dollars can be most efficiently spent.

Material and methods

Lake Superior is located in the headwaters of the Great Lakes watershed and is bordered by Ontario to the north and Minnesota, Wisconsin and Michigan to the west and south. It has the highest surface elevation, largest total water volume, and greatest depth of the five Great Lakes (Fuller and Shear, 1995). Due to the relatively undeveloped nature of the watershed, Lake Superior has the lowest concentration of open water phosphorus, and, although the status of nearshore phosphorus likely is also low, it has not yet been assessed (EC, Environment Canada and USEPA, United States Environmental Protection Agency, 2009). Lake Michigan is the only lake located entirely within the United States, bordered by Wisconsin, Michigan, Illinois, and Indiana, and it has higher nutrient and pollutant loadings than Lake Superior. Lake Michigan is the second largest Great Lake by volume with the second greatest maximum depth. The current status of open water phosphorus concentration is rated as good with an improving trend in Lake Michigan, while nearshore phosphorus concentration remains poor (EC, Environment Canada and USEPA, United States Environmental Protection Agency, 2009). We used multiple landscape data types to describe the conditions present in watersheds of Lakes Superior (U.S. only) and Lake Michigan. Only the U.S. side was included in our modeling because comparable datasets for predictor and response variables (with the exception of forest disturbance data) were not readily available for the Canadian watershed of Lake Superior.

Water quality data

Water quality data were retrieved from EPA's STOrage and RETrieval (STORET) database and USGS's National Water Information System (NWIS). We augmented the water quality data for Lake Superior with collections from the Wisconsin Department of Natural Resources. The study interval was limited to the years 2005 to 2009 to overlap with the landscape data, especially the recent forest disturbance class and the forest inventory data, and to limit the amount of climatic variation occurring during the interval. To model the most active period of stream flow when the transport of large quantities of nutrients and turbidity (i.e., sediment) occurs, the models described the spring runoff period (March to June; Detenbeck et al., 2003). Multiple water quality variables were available for the basins, but after considering the spatial and temporal availability, along with the number of observations for each variable that was below the minimum detection limit, we selected two: total phosphorus (mg/L) and turbidity (NTU). Total phosphorus (TP) is a commonly collected primary nutrient variable in monitoring programs and is associated with enrichment from human sources. Turbidity is a measure of water clarity and was selected, as opposed to total suspended solids, because there was acceptable temporal and spatial coverage of the data and no samples were below the minimum detection limit. In the Lake Michigan watershed, NTU data were available at fewer sites than TP, so there were fewer watersheds (23) with NTU observations to use in the modeling. We modeled concentrations rather than loads (quantity delivered per unit time) because stream flow data were not available for all watersheds. By focusing on the hydrologically-active spring season, we should indirectly account for the periods when the greatest amounts of nutrients and sediments are entering the nearshore areas of the lakes.

Landscape data

Principal components analysis was used to identify collinearity between continuous landscape variables (Table 1), and some were excluded because of redundancy. The loadings of each variable on the first two principal components were examined graphically, and we provide details on which variables were excluded below. The selected variables were then used to build models to predict water quality. Data were obtained from multiple sources and summarized in ArcMap (version 9.3.1, Redlands, CA) using the Spatial Analyst extension. General boundaries for the Lake Superior and Michigan watersheds were defined by the 10 digit Hydrologic Unit Code (HUC10) from the Watershed Boundary Dataset (http://datagateway.nrcs.usda.gov, Accessed July 19, 2010). We used the National Hydrological Dataset Plus (NHDPlus; http://www.horizon-systems.com/nhdplus/index.php, accessed 25 June 2010; USGS, U.S. Geological Survey, 2009) to characterize the stream network. Artificial paths (i.e., artificial connections through lakes and impoundments) were removed, because we were only interested in actual streams in relation to water quality stations.

Table 1
Study watershed summary of proportion of landscape variables for Lake Superior and Lake Michigan. Landscape variables are Vegetation Change Tracker (VCT; persistent forest, disturbed forest 1984–1999, and disturbed forest 2000–2009), National Land Cover Dataset 2006 (NLCD; agriculture, urban, and watershed storage), and Forest Inventory and Analysis (FIA; softwood). The table only contains variables that were selected for the final models and not all the variables considered.

Lake	Variable	Landscape variable	Mean	SD
Superior	Total phosphorus	Persisting forest	0.77	0.15
		Disturbed forest 2000–2009	0.03	0.02
		Agriculture	0.03	0.05
	Turbidity	Persisting forest	0.80	0.12
		Disturbed forest 2000–2009	0.04	0.02
		Agriculture	0.03	0.05
		Urban	0.02	0.06
Michigan	Total phosphorus	Disturbed forest 1984–1999	0.02	0.02
		Watershed storage	0.18	0.15
		Urban	0.14	0.22
	Turbidity	Disturbed forest 2000–2009	0.01	0.01
		Softwood	0.08	0.11

We calculated watershed drainage intensity as a metric of area watershed's drainage potential (drainage intensity = stream length (km)/watershed area (km^2)).

A recently completed Vegetation Change Tracker (VCT) database for the entire Lakes Superior and Michigan basins was used to describe forest persistence and disturbance (Stueve et al., 2011). VCT is an algorithm which uses time series stacks of Landsat images to detect persisting nonforest, persisting forest, and water, as well as disturbed land cover as a 30-meter raster (Huang et al., 2009); in our case, the raster identified two disturbance intervals: 1984 to 1999 and 2000 to 2009. Persisting categories represent pixels that did not change classes during the period 1984–2009. The disturbed areas were pixels that changed from forest to nonforest during the time period covered by Landsat imagery, but VCT does not reveal the ultimate fate of those lands after the disturbance (e.g., return to forest or a permanent conversion to other land use).

The most recent version of the National Land Cover Dataset (NLCD2006; http://www.mrlc.gov/nlcd2006.php, accessed 28 March 2011; Fry et al., 2011) was used to quantify four general land cover classes for consideration as predictors (agriculture, urban, and watershed storage). Of the original 15 land cover classes observed in the two basins, we retained agricultural (pasture and cultivated), and urban (low, medium, and high density developed land). The combined agricultural and urban land covers were highly correlated with persisting nonforest derived from VCT, so we retained the more informative pair of NLCD variables for modeling. The nonforest variable from VCT also included wetland areas that were neither forested nor developed, so using the NLCD agriculture and urban was the best measurement of human development in the watersheds. Other classes observed in the basins were: open water, developed open space, barren, forest, shrub, grassland, and wetland, but were not considered individually as predictors in the models. We computed watershed storage from NLCD variables by combining the proportion of area classified as open water and wetland in each watershed. Another measure of urban development, USGS 2006 percent developed impervious (http://www.mrlc.gov/nlcd06_data.php, accessed 3 March 2011), was highly correlated with NLCD's urban class. Although it has been argued that impervious surface is a better indicator of urban degradation (Arnold and Gibbons, 1996), we selected the NLCD urban metric for consistency with NLCD agriculture. In the case of the urban land for the Lake Michigan TP sites, we found that there was a threshold at 14% urban land use where increasing urban area was no longer associated with increased observed TP concentrations. A comparison of model performance between the 14% urban threshold and using all the observed urban values showed better overall model performance when using the urban threshold, so it was retained in the Lake Michigan TP model.

We used proportion of softwoods and proportion of hardwoods as two predictor variables reflecting forest composition. These data were based on the USDA Forest Service's Forest Inventory and Analysis plot data, which were generalized into a continuous surface raster dataset (Wilson et al., 2009, 2012). Details on the plot data collection and tree species in forest type groups are available in Woudenberg et al. (2010). We collapsed the thirteen observed forest type groups into softwoods and hardwoods in order to use forest type information parsimoniously. The total proportion of each group was calculated for each watershed and used in the analysis.

Watersheds were also categorized into ecoregions using the USDA Forest Service Province and Section classification (http://www.fs.fed.us/rm/ecoregions/ and http://fsgeodata.fs.fed.us/other_resources/ecosubregions.php, Accessed July 22 2010; McNab et al., 2005; Fig. 1). We use the division, province, and section level of ecoregion classification developed for the continental United States by the U.S. Forest Service. The division classified land by regional climate differences, while the province reflected the potential of natural vegetation in the area (McNab et al., 2005). There were two overlapping Divisions and Province in the study area; the Lake Superior basin and the northern Lake Michigan basin in the Laurentian warm continental division and mixed forest province (212); while the southern half of the Lake Michigan basin was in the hot continental division and Midwest broadleaf forest division. The watersheds were divided to an additional level by sections (indicated by a letter following the province) while described the geologic stratigraphy and lithology, and soils (McNab et al., 2005). The Lake Superior sections were grouped into four categorical variables in order to provide fairly homologous areas for the assignment of membership to watersheds. The ecoregion groups were primarily a geographical gradient from west to east along Lake Superior, but these groups also captured the differences in soils (e.g., Lake Superior clay plain in 212 K) that were present. It was a logical division to separate the Lake Michigan watershed to the north and south by the division and province. Further study of the sections indicated that the 222 province could be separated into two groups on either side of the lake, while the eastern 212 was also a single section. To minimize the number of groups in the analysis, we assigned the remaining 212 sections to a single class (212 west). Lake Michigan was divided into four categorical ecoregion groups based on province and orientation to the Lake (212 E, 222 E, 212 W, 222 W). East and west were defined with a hypothetical line dividing the lake from Lake Huron in the north, through the center of the Lake to the most southern point on Lake Michigan between the HUCs 04040001 and 04040002. Watersheds with mixed provinces were assigned to the ecoregion in the majority. The percentage of NLCD agriculture and urban was calculated within each ecoregion using GIS.

New watershed delineation

Before landscape information could be summarized, watersheds needed to be delineated for each site where total phosphorus or turbidity was collected (gauged sites), along with other parts of the Great Lake basins that did not have available water quality data (ungauged sites). Portions of the watershed, mostly small coastal areas, were not delineated because they did not contain a stream network larger than 1 km^2 (i.e., the minimum gauged watershed size) or lacked a direct link in NHDPlus to the lake. We used Arc Hydro Tools 9 (ESRI, Redland, CA) to delineate watersheds draining to the coordinates of each water quality station following standard procedures outlined by ESRI (2005). The 1 arc second National Elevation Dataset (NED; http://seamless.usgs.gov/ned1.php, accessed 29 June 2011) was used for the digital elevation model. We utilized established stream paths (NHDPlus) and watershed boundary (HUC10) to maintain consistency between the new watersheds and available hydrology (ESRI, 2005). The NHDPlus stream layer was used to lower the DEM along the stream path, which resulted in Arc Hydro mapped streams

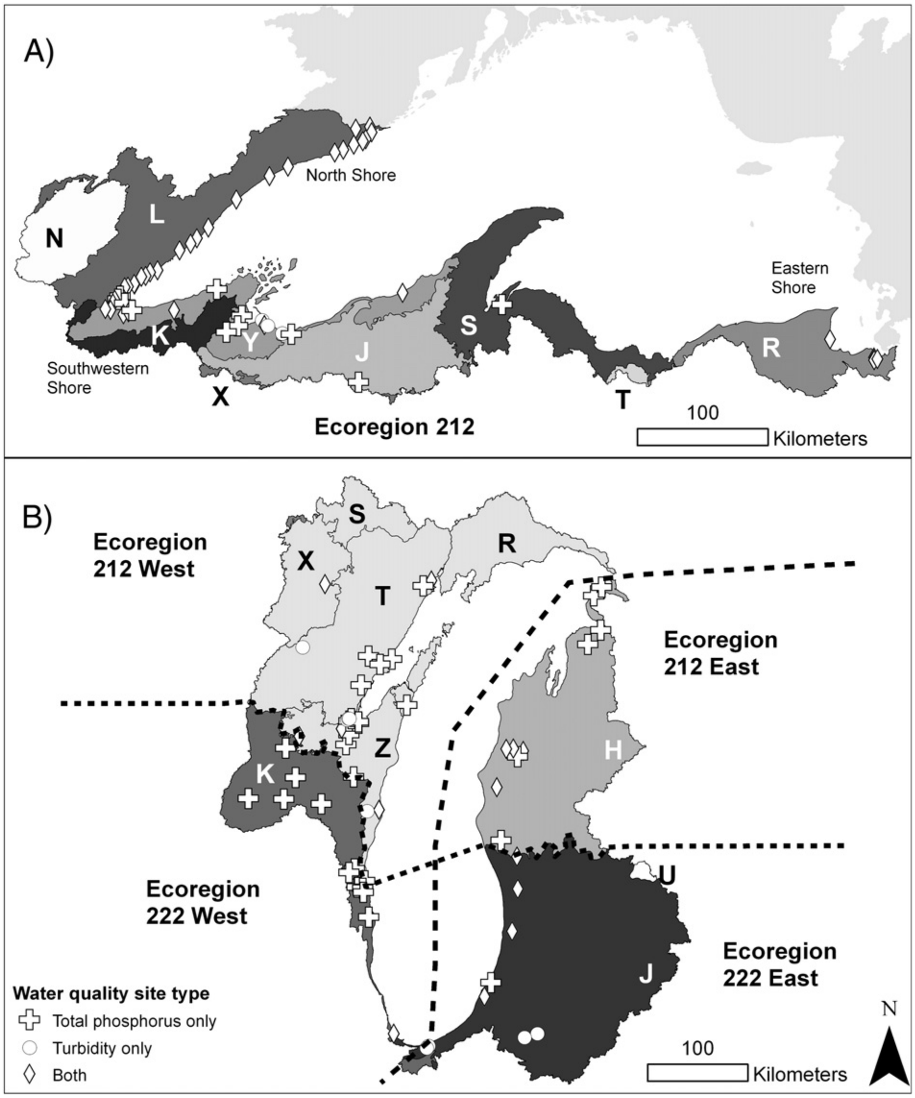

Fig. 1. Ecoregion groups and location of water quality sampling sites for A) Lake Superior and B) Lake Michigan. Symbols show type of water quality sampled (total phosphorus only, turbidity only, or both). Delineations of the ecoregion groups for Lake Michigan are shown with dash lines (222 east, 222 west, 212 east, and 212 west). Ecoregions were divided into provinces (numbers), which were subdivided into sections (letters), see Material and methods for additional information.

agreeing with NHDPlus. The outlines of HUC10 were used to build inner walls in the DEM, which kept delineated watersheds in agreement with HUC10 boundaries. Area (km^2) was calculated in ArcMap for each watershed. To increase sampling size and reduce the influence of correlation from nested watersheds, we only included nested watersheds for Lake Michigan when they were a small proportion of the larger watershed.

Water quality modeling

In both basins, the sample distributions of TP and NTU values were highly right-skewed and ranged over multiple orders of magnitude, so we log-transformed all TP and NTU values. Also, because the minimum NTU observed in Lake Michigan was zero, we added a constant (0.5; i.e., half the minimum non-zero NTU value) to each NTU observation for Lake Michigan before transformation (Gotelli and Ellison, 2004). Because repeated measurements of water quality were taken from many watersheds, we expected more similarity within a watershed than between watersheds. Also, within a single site we expected observations taken during the same year to be more similar if they were taken on days close together than if they were take on days far apart. These expectations suggested using a mixed-effects regression model, where *i* represented a site, *j* represented a year, and *k* represented a day in the following model:

$$Y_{ijk} = X_i\beta + u_i + v_{ij} + \epsilon_{ijk}$$

where Y_{ijk} is an observed value, X_i is a vector of landscape variables, β is a vector of coefficients describing the relationship between landscape and water quality, u_i is a random intercept for site, v_{ij} is a random intercept for a year within a site, and ϵ_{ijk} is measurement error. We assumed that the random intercepts for site and year within each site are independent normal random variables. We also assumed that the measurement errors were normal, and may be correlated (with a first-order autoregressive structure) if they correspond to observations taken from the same site in the same year, but are otherwise independent.

To estimate the parameters in this model, we followed the same general approach for TP and NTU. The statistical software R (version 2.13.2; R Development Core Team, 2011) and the *lme* function in the *nlme* package (version 3.1-102; Pinheiro et al., 2011) were used to fit all models. First, we included in X_i all the landscape variables described above, then fit models with a variety of random effects structures (all special cases of the model described above) using restricted maximum likelihood, and, finally, compared them using likelihood ratio tests. In Lake Superior, for both TP and NTU, a model including both random intercepts (u_i and v_{ij}) was found to fit better than models lacking these terms. Also, a first-order continuous autoregressive correlation between measurement errors within the same site (ϵ_{ijk}) improved the fit, and was kept in the model. In Lake Michigan, for both TP and NTU, tests suggested that only the random intercept for site (u_i) was necessary, so the intercept for year within site (v_{ij}) was discarded from the model. However, the first-order continuous autoregressive correlation of measurement errors within the same site and year (ϵ_{ijk}) still improved both fits and was kept.

Next, we determined the landscape variables to be included in the landscape variable vector (X_i) by backwards elimination. A sequence of models (all containing the same error structure as set above) were fit using maximum likelihood where the least significant predictor (as measured by the p-value testing if its coefficient was non-zero) from the previous model was removed. This sequence was extended until all coefficients were estimated with significance (p-value < 0.05). We then studied the likelihood ratio tests comparing adjacent models in sequence to select a model that balanced parsimony with fit, and made sense from an ecological perspective. The information in the Akaike information criterion and Baysian information criterion supported the model selection decisions. The chosen model for each response/lake combination was then refit using restricted maximum likelihood. The models were then used to predict the TP and NTU at gauged and ungauged sites in both lake basins. Gauged site estimates included predicted site-specific effects ($\hat{u}_i$), while ungauged site estimates were based on the landscape composition only. Goodness of fit for the models was measured between the population-level fitted values (based on landscape composition only) and the mean response as a measure of how much additional variability was explained by the predictors. Goodness of fit was defined as the difference between the estimated site-level variance of a null model where no predictors were used and the estimated site-level variance of a fitted model using the landscape predictors, as defined in the following:

$$R^2_{site} = 1\text{–}Variance_{fitted}/Variance_{null}$$

We chose to ignore within-site variability when assessing model fit because our landscape data were constant within site and because we are primarily interested in the typical water quality at a given site, rather than the expected water quality on a given day at a given site. The reduction of site-level variance is analogous to a squared correlation ($R^2{}_{site}$) value and represents the percentage of site-to-site variability in water quality that is being explained by the models. In order to demonstrate the importance of individual predictors to the estimated water quality values, we conducted a series of model predictions with a range of predictor values. Each predictor was changed by set amounts (+/− 1–5%), and then the predicted values were compared to a baseline value equal to the mean landscape composition of the model watersheds (Table 1). We used the Mantel test to quantify spatial autocorrelation between the model residuals and spatial location with the *mantel.rtest* function (with 10,000 permutations in the p value calculation) in the *afe4* package in R. There was a slight correlation only in the LS TP model (0.23, p = 0.03, n = 457), so we proceeded with the modeling with the understanding that there was a small amount of autocorrelation.

For the purpose of prioritizing risk, watersheds were grouped with different criteria for gauged and ungauged model outputs. We understood the error structure for the models of the gauged sites and grouped them by the predicted concentrations. We selected two general thresholds to group data after observing the current water quality criteria in the states bordering Lakes Superior and Michigan (e.g., Wisconsin TP <0.075 mg/L for streams and <0.1 mg/L for rivers; current standards available at USEPA, U.S. Environmental Protection Agency, 2011). The risk group thresholds for TP were 0.05 and 0.075 mg/L, while for NTU we used 10 and 25 NTU (based on Minnesota NTU standard levels) for gauged rivers. Because of the multijurisdictional nature of the Great Lakes basin, no single water quality criterion will apply to an entire Lake, but the levels we selected should be informative in the management of the basin's aquatic resources. We chose not to map ungauged areas by predicted concentration because we suspected that gauged sites would tend to have higher concentrations than ungauged sites. In other words, we believe that our sample of watersheds is biased. Instead, we used predicted concentrations to rank the watersheds based on the potential risk to water quality based on the landscape. These rankings are based on the assumption that the relationships between the landscape predictors and water quality are the same at the gauged and ungauged locations. The groups were conservatively assigned as low risk (0–74th percentile), moderate risk (75–89th percentile), and high risk (90–100th percentile). We plotted the predicted values for each model from minimum to maximum, and these figures were used to guide the selection of the risk thresholds, which showed small differences in low group concentrations, higher concentrations in the moderate group, and highest concentration in the high group (between group differences were significant). These groups were judged to be the best way to objectively classify groups, while also providing useful differences between groups of watersheds. Although these groups were based on percentiles, the differences in the predicted values were large and would be useful for selecting sites for management actions.

In order to assess the relationship between our TP model and SPARROW TP model, we obtained flow-weighted TP (mg/L) from the SPARROW Decision Support System for the Great Lakes model (USGS Major River Basin 3; http://water.usgs.gov/nawqa/sparrow/dss/, accessed January 5, 2012). The SPARROW model TP estimates describing the base year of 2002 in Lakes Superior and Michigan were available for most gauged watersheds, and we selected the TP concentration that most closely corresponded to the location of a gauged water quality location. The SPARROW and gauged watershed concentrations were transformed with the natural logarithm to obtain normal distributions before comparisons. We calculated Pearson correlation coefficients and linear regression for the paired dataset of the SPARROW and gauged estimates in R (version 2.13.2; Development Core Team, 2011).

Results

Data description

We used data collected at 49 sites for total phosphorus (TP) and 41 sites for turbidity (NTU) in Lake Superior, and 47 sites for TP and 23 sites for NTU in Lake Michigan. Mean watershed size was 475 km^2 for TP and 539 km^2 for NTU in Lake Superior (range: 3–9, 158 km^2), while in Lake Michigan mean watershed size for TP was 1,976 km^2 and NTU was 2684 km^2 (range: 1–16, 410 km^2; Table 2). Mean gauged site TP was 0.08 mg/L and mean NTU was 62.6 NTU in Lake Superior tributaries (Table 3). The mean gauged site TP was 0.15 mg/L and mean site NTU was 15.4 NTU in Lake Michigan. Median TP and NTU were lower than mean values but the patterns between basins were the same (Table 3).

The mean proportion of persisting forest was large in the Lake Superior basin (0.77 for TP watersheds and 0.80 for NTU watersheds; Table 1). The larger proportion of forest in the Superior basin was associated with a larger amount of disturbed forest (2000–2009), while Lake Michigan had lower quantities of disturbed forest (disturbed forest 1984–1999 and 2000–2009). Land cover patterns from the NLCD reflected the forest disturbance data with small proportion of urban (0.02 in NTU watersheds) and agricultural land (0.03 in both models) in Lake Superior, and a larger proportion of urban in the Lake Michigan basin (0.12; Table 1). Ecoregion 212 was the only province present in

Table 2
Summary of mean size, minimum size, maximum size, and standard error of watersheds used in modeling total phosphorus and turbidity in Lake Superior and Lake Michigan.

Water quality variable	U.S. Lake Superior	Lake Michigan
Total phosphorus		
Mean (km^2)	474.9	1975.7
Min (km^2)	3.3	1.1
Max (km^2)	9158.4	16,410.2
Standard error	205.0	546.0
n	49	47
Turbidity		
Mean (km^2)	539.1	2684.3
Min (km^2)	3.3	1.0
Max (km^2)	9158.4	13,591.2
Standard error	243.8	776.9
n	41	23

the Superior basin, and was subdivided into nine sections (Fig. 1). Lake Michigan had two ecoregion provinces (212 and 222), with area approximately divided between the two (0.58 in ecoregion 212, and 0.42 in ecoregion 222), although there was more area in 222 to the east of Lake Michigan than to the west (Fig. 1).

Model development

Table 4 presents the model $\hat{\beta}$ values that are the estimated fixed effect coefficients, along with the lower and upper bounds of 95% confidence intervals and p-values for individual predictors for each model. Although some predictors had p-values greater than 0.05, variables were not solely selected based on p-values; we also considered the overall fit of the model, which was reduced when the non-significant predictors were removed. We quantified the relative importance of each predictor to estimated water quality values (Fig. 2). For Lake Superior, the selected TP model used the proportion of persisting forest, forest disturbed during 2000–2009, and agricultural land as predictors, and the NTU model used the proportion of persisting forest, forest disturbed during 2000–2009, agricultural land, and urban land as predictors. In both Lake Superior models, there was a positive relationship between predictors and estimated water quality, where an increase in the proportion of land use resulted in an increase in TP or NTU. Agriculture and disturbed forest 2000–2009 were the most influential predictors in Lake Superior for TP (Fig. 2a) and NTU (Fig. 2b). The magnitude of change was less in the TP model than the NTU model, where an increase of 5% of agriculture or disturbed forest resulted in an increase in TP of >40% and nearly 30%, respectively. For the NTU model, an increase of 5% disturbed forest 2000–2009 resulted in nearly 300% increase in NTU, while a similar increase in agriculture had nearly 200% increase in NTU. For Lake Michigan, the TP model used ecoregion, the proportion of disturbed forest during 1984–1999, watershed storage, and a threshold response of the proportion of urban land as predictors, and the NTU model used ecoregion, and the proportion of forest disturbed during 2000–2009 and the proportion of softwood forest as predictors. The most influential predictor for TP in Lake Michigan was ecoregion, while within each ecoregion disturbed forest 1984–1999 had slightly more influence than storage and urban area (Fig. 2c). Increased disturbed forest 1984–1999 and storage were related to lower TP, while % urban had a positive relationship with TP. In the Lake Michigan TP model, the threshold response of % urban was used after observing scatterplots of the relationship with TP. The threshold was set at the mean proportion of urban land (0.14) in Lake Michigan TP gauged watersheds, where the model used the mean proportion for watersheds with more than 14% urban areas. The Lake Michigan NTU model was influenced more by increases in disturbed forest 2000–2009 than changes in softwood (Fig. 2d). There was a large positive relationship between NTU and forest disturbance 2000–2009, while the proportion of softwood was negatively related to NTU. All the models included forest as useful indicators in determining the status of water quality in the tributaries, while the influence of human development was also reflected in the models directly (agriculture and urban) and indirectly (ecoregion).

Table 3
Mean, median, minimum, maximum, and standard deviation for tributary sampling site total phosphorus and turbidity in the Lake Superior and Lake Michigan basin.

Water quality variable	U.S. Lake Superior	Lake Michigan
Total phosphorus (mg/L)		
Mean	0.08	0.15
Median	0.04	0.08
Minimum	0.01	0.01
Maximum	0.72	1.05
Standard deviation	0.13	0.21
n	49	47
Turbidity (NTU)		
Mean	62.6	15.4
Median	20.6	9.3
Minimum	2.9	2.1
Maximum	641.6	70.0
Standard deviation	112.5	16.1
n	41	23

The major ecoregion groups for the Lake Michigan watershed, 212 and 222, demonstrated the differences between the less developed (i.e. urban and agricultural land use in NLCD) northern part and the more developed southern part of the basin. There was less urban in the north (212: 2.7% in the east and 2.4% in the west) than the south (222: 8.3% in the east and 10.3% in the west). There was a similar pattern in ecoregion 222 for agriculture with less in the north (212: 16.2% in the east and 20.1% in the west) and more in the south (222: 51.8% in the east and 46.6% in the west). There was a temporal lag associated with the older forest disturbance (1984–1999) in the Lake Michigan TP model, so we overlaid the areas of older disturbance in the gauged watersheds over the recent land cover (i.e., NLCD). The overlay summary showed that a majority (78%) of the area of forest disturbed in 1984–1999 was in an undeveloped state (e.g., 45% forest, 16% grassland and shrubs, 16% wetland) compared to areas that were developed (22%). In the developed areas, a large overall part of the landscape was urban open space (6%), with only 14% overall land that became a potential nutrient source (4% low and moderate urban development and 10% agricultural lands).

We show the relationship between fitted and observed values on the natural log scale for Lake Superior and Lake Michigan (Fig. 3). The population-level fitted values in Fig. 3 are based only on information contained in the predictors, and do not include predicted values of random effects. For Lake Superior, the R^2 between the observed and predicted values was 0.23 for TP and 0.58 for NTU. In Lake Michigan, the R^2 were 0.77 for TP and 0.43 for NTU. The models did a reasonable job of explaining variability in water quality using only watershed-scale variables. Comparing the variance of the fitted to the null model R^2_{site} indicated that the models explained at least half of the variation in the mean water quality values with the lowest value for Lake Superior TP (49%) and highest for Lake Michigan TP (76%; Table 5). The NTU models explained a similar amount of variation in both lakes (64%; Table 5).

Model predictions

Fig. 4 presents the predicted TP and NTU for gauged watersheds (i.e., watersheds with observed water quality values and site-specific effects in models), and estimated ranks of ungauged sites (no observed water quality and no known site-specific effects) for Lake Superior. The five watersheds with the highest observed mean TP (>0.075 mg/L) were located in southwestern Lake Superior and two watersheds in the east (Fig. 4A). The middle range of gauged

Table 4
Landscape variables and associated β for total phosphorus and turbidity models in Lake Superior and Lake Michigan. Upper and lower bounds report 95% confidence intervals on β. P-values for each variable are also reported.

Lake	Water quality	Landscape variable	Lower	β	Upper	p-value
U.S. Lake Superior	Total Phosphorus	(Intercept)	−3.49	−3.33	−3.18	<0.01
		Persisting forest	−0.38	1.01	2.40	0.15
		Disturbed 2000–2009	−1.89	5.25	12.39	0.15
		Agriculture	3.11	7.04	10.97	<0.01
	Turbidity	(Intercept)	2.39	2.64	2.88	<0.01
		Persisting forest	4.05	8.92	13.79	<0.01
		Disturbed 2000–2009	14.62	27.12	39.61	<0.01
		Agriculture	12.71	21.83	30.94	<0.01
		Urban	−0.27	8.21	16.68	0.06
Lake Michigan	Total phosphorus	Ecoregion e212	−3.53	−3.03	−2.54	<0.01
		Ecoregion e222	−3.23	−2.76	−2.28	<0.01
		Ecoregion w212	−2.58	−2.25	−1.93	<0.01
		Ecoregion w222	−2.34	−2.07	−1.80	<0.01
		Disturbed 1984–1999	−26.50	−16.55	−6.60	<0.01
		Watershed storage	−3.39	−2.19	−0.99	<0.01
		Urban (threshold)	−0.41	4.04	8.49	0.07
	Turbidity	Ecoregion e212	1.90	2.35	2.81	<0.01
		Ecoregion e222	1.24	1.65	2.06	<0.01
		Ecoregion w212	2.14	2.64	3.15	<0.01
		Ecoregion w222	1.74	2.37	2.99	<0.01
		Disturbed 2000–2009	1.50	33.08	64.65	0.04
		Softwood	−11.37	−7.19	−3.00	<0.01

watersheds for TP includes three large western watersheds and a cluster of smaller watersheds along the north shore of Superior. Moderate to high risk watersheds were located mainly in the southwestern part of the basin. The NTU model outputs (Fig. 4B) show a larger number of watersheds in the high group of observed NTU than was observed with TP. The watersheds with the highest NTU values were located in the southwestern portion of the basin, especially in the Nemadji River watershed. Moderate NTU values were present in watersheds along the north shore of the western arm and the St. Louis River. Ungauged watersheds in the high groups

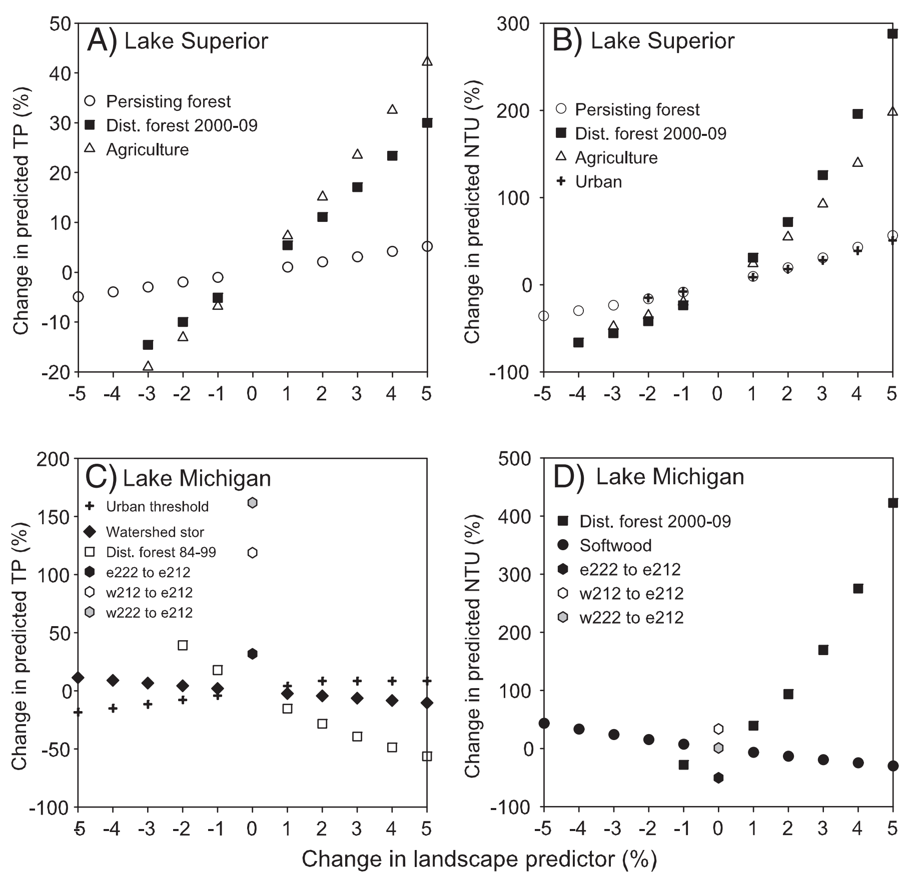

Fig. 2. Relative influence of changes in landscape predictor on water quality models in Lake Superior (A) TP and (B) NTU, and Lake Michigan (C) TP and (D) NTU). Lake Michigan models include the relative differences in estimates at the baseline (i.e., mean landscape estimates) configuration. Symbols correspond to persisting forest (open circle), softwood (closed circle), disturbed forest 1984–1999 (open square), disturbed forest 2000–2009 (closed square), agriculture (open triangle), urban (plus), watershed storage (diamond), ecoregion e222 relative to e212 (closed hexagon), ecoregion w212 relative to e212 (open hexagon), and ecoregion w222 relative to e212 (gray hexagon).

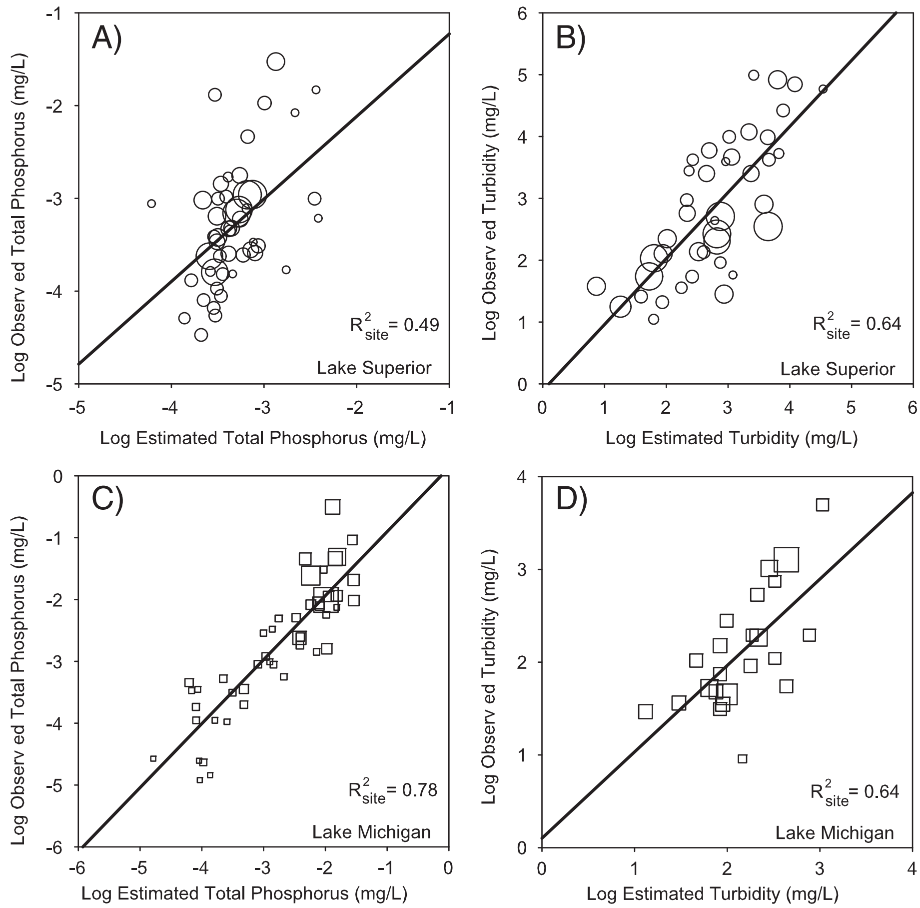

Fig. 3. Linear regressions of observed and estimated mean water quality values for total phosphorus and turbidity in Lake Superior (circles; A and B) and Lake Michigan (squares; C and D). Symbol size is proportional to the sampling size for each watershed calculated as relative symbol size $= (n_i/n_{max})^{1/2}$, where n_i is the number of observations in site *i* and n_{max} is the maximum number of observations for any one site. R^2_{site} values are reported based on the variance reduction between null model (without landscape predictors) and fitted model (with landscape predictors).

were in the southwest part of the basin, similar to the TP model for ungauged watersheds.

In Lake Michigan, TP was highest in the western watersheds for both the gauged and ungauged sites (Fig. 5). Gauged TP concentrations were also elevated in the watersheds on the eastern side of Lake Michigan. The ungauged watersheds on the south and west side of the lake were expected to have higher TP concentrations, although most of the smaller ungauged watersheds in the southeastern part of the basin were in the low risk group (Fig. 5A). The eastern gauged watersheds had intermediate NTU levels, while the highest NTU was in the small west central watersheds (Fig. 5B). Smaller ungauged watersheds in the western watersheds along the middle lake (and into Door County peninsula) were predicted to have the highest risk of elevated NTU. There were three small watersheds in the high risk category and six watersheds in the moderate risk category for NTU for ungauged watersheds on the eastern side of the Lake.

Table 5
Estimated variance of null model with no predictors, full model with predictors, and the estimated variance reduced by fitted model. Variance reduction was analogous to an r-squared value for the models.

Lake	Water quality	Null model variance	Fitted model variance	Variation explained by fitted model
U.S. Lake Superior	Total phosphorus	1.011	0.228	77.5%
	Turbidity	0.208	0.075	63.8%
Lake Michigan	Total phosphorus	0.127	0.065	49.1%
	Turbidity	0.813	0.296	63.6%

SPARROW estimates in gauged watersheds

There was a significant correlation between our TP predictions and the flow-weighted TP concentrations estimated by the SPARROW model. The correlation was weaker in Lake Superior ($r = 0.62$; $n = 38$; $p < 0.01$) than in Lake Michigan ($r = 0.88$; $n = 47$; $p < 0.01$). Linear regressions were also significant for both Lakes (Fig. 6).

Discussion

We developed models using landscape variables to predict two common water quality variables, total phosphorus and turbidity, with particular emphasis on the role of landscape composition and forest disturbance metrics. Landscape variables explained the variation in water quality to various degrees, from 49 to 78%, with only watershed-scale landscape data used in the model. In comparison to other studies that modeled water quality using linear mixed models, our models explained a comparable degree of variation using landscape variables. In models for a single California watershed (Cosumnes River), variation explained was similar (nitrate 47%) or higher (total suspended solids, a measure of water clarity; 93% variation; Ahearn et al., 2005), while for models of streams in Puerto Rico the amount of variation explained was similar to our models (TP 58% and NTU 32%; Uriarte et al., 2011). Models for instream concentrations of fecal bacteria were

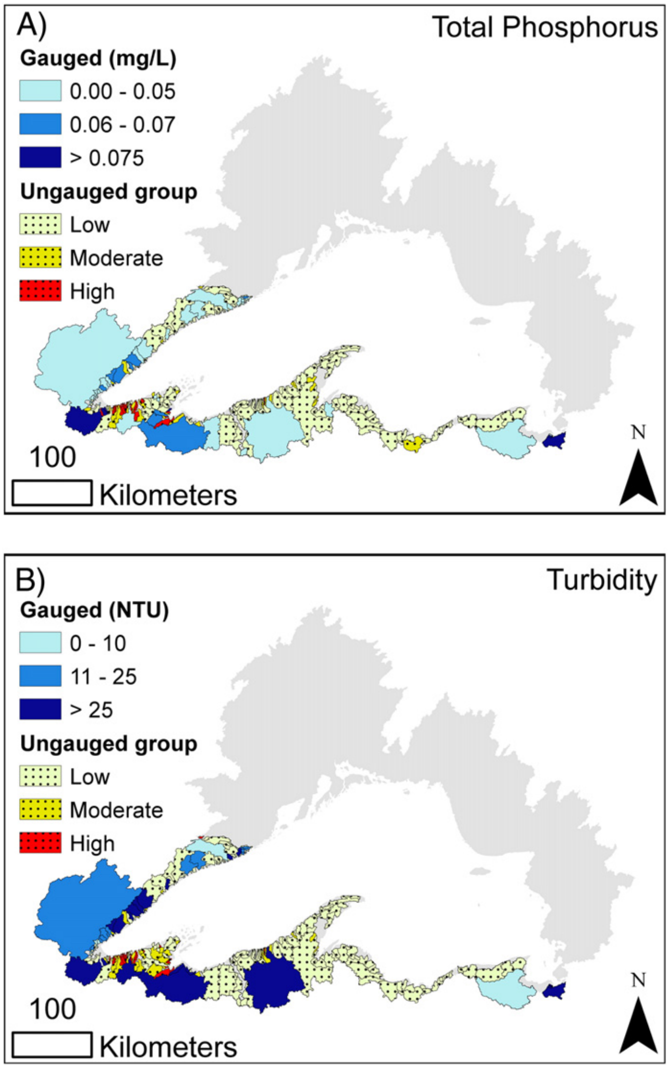

Fig. 4. Modeled spring runoff A) total phosphorus (mg/L) and B) turbidity (NTU) for watersheds with observed values (gauged) and based on landscape variables only (ungauged) for Lake Superior. Gray areas are the portions of the basin not modeled.

also similar to our models, with 70% variation in *Enterococcus* concentration explained for Hawaiian streams (Ragosta et al., 2010) and 49% variation in fecal cattle concentration in California streams (Tate et al., 2003). The low r-squared for the Lake Superior TP model indicate that the set of landscape variables that we included did not explain the patterns in TP very well, so future research is needed to identify the important predictors of TP. This study represents the first use of vegetation change tracker (VCT) metrics to model water quality. VCT provides novel metrics with both spatial and temporal components, such as persisting forest and nonforest, along with forest disturbance classes. Our use of VCT data also accounted for the temporal status of forest rather than simply the current status of the land cover, such as persistent forest factor, which has added value compared to simply a snapshot of forest (e.g., NLCD land use).

We developed models that identified a mix of landscape predictors in relation to water quality, including human development, forest, and large scale ecological classifications. Models of TP and NTU in Lake Superior both included persisting forest and recently disturbed forest, which were both retained because they resulted in a better overall fit of the model, even though they had p-values of 0.15. The Lake Superior watershed is heavily forested, with little agricultural and urban land, so it was not unexpected to have forest predictors strongly linked to changes in TP and NTU. However, when human development, especially agriculture, was present in a watershed, it was closely linked with increased TP and NTU. Detenbeck et al. (2004, 2005) reported that watersheds with less mature forest (<50%) had 3 times higher NTU than watersheds with more mature forest, but our results were not able to support or reject these findings. Our dataset only contained 2 watersheds with persisting forest below 50%, so conclusions could not be drawn. The differences in seasonal and regional NTU between the studies may also be a factor, Detenbeck et al. (2004) reported that north shore, low forest (<50%) watersheds in Lake Superior had elevated NTU values in spring, and south shore, low forest watersheds had elevated NTU in summer; our study used only water quality from the spring runoff period and had a larger spatial area.

Ecoregion was included as a categorical variable in the models for both Great Lakes, although only the Lake Michigan model selection process included ecoregion in the final models. The ecoregion divided Lake Michigan into four roughly equal size units, where the water quality observations were more similar within the ecoregion than between the ecoregion. Within the framework of the model, ecoregion provides a range of potential starting points for estimated concentrations because ecoregion does not change through time, and some ecoregions have higher concentrations than others. Thus, the changes in landscape variables of the same proportion of the landscape will be different in each ecoregion. These ecoregion specific models will allow managers to look at specific landscape changes in their region, which may be more effective for management planning. The division of the watershed by ecoregion boundaries was also likely to incorporate basin-scale differences in land use, with a greater proportion of agriculture and urban in the southern ecoregion 222 than in the northern ecoregion 212. This difference in general patterns is important to keep in mind while discussing the other predictors that were included in the Lake Michigan models. The percentage of agriculture has been linked to water quality elsewhere (Riseng et al., 2010), and we do not suggest that agriculture was not important in the Lake Michigan models; rather the difference in ecoregion (i.e., ecoregion differentiating between developed and undeveloped parts of the entire watershed) was identified as a better predictor in these models by the stepwise method than the observed percent agriculture. Spatial scale may also account for the improved model fit provided by the section of ecoregion rather than percentage agriculture; we aggregated land use across whole watersheds, while ecoregion was also a generalization of the entire lake basin into large units with similar climate and soils. It is worth noting that the differences in agriculture and urban land uses also are captured by the ecoregions. Future models may benefit from including riparian land use and the specific type of farming (e.g. row crops) and riparian buffers; these may be a better representation of the true impacts of land use on water quality. Within each ecoregion, forest cover was important in Lake Michigan watersheds, with the only occurrence of forest disturbed during 1984–1999 in the TP model. The land with older disturbance was mostly undeveloped land, and was not contributing high amounts of TP to waterways. The relationship between the location of tributaries and the nearshore water quality has been documented (Twiss and Marshall, 2012). The location of higher TP concentrations in tributaries are in areas where there is elevated nearshore TP (e.g., eastern shore of Lake Michigan) as reported in the State of the Lakes Ecosystem Conference report (EC, Environment Canada and USEPA, United States Environmental Protection Agency, 2009). The Lake Michigan NTU model identified the importance of forest composition with the softwood and recently disturbed forest variables. The forest disturbance data did not differentiate between natural and anthropogenic forest disturbance, so a future improvement to the dataset should link cause of disturbance to time period. Additional research is needed to better understand the relationship between recent

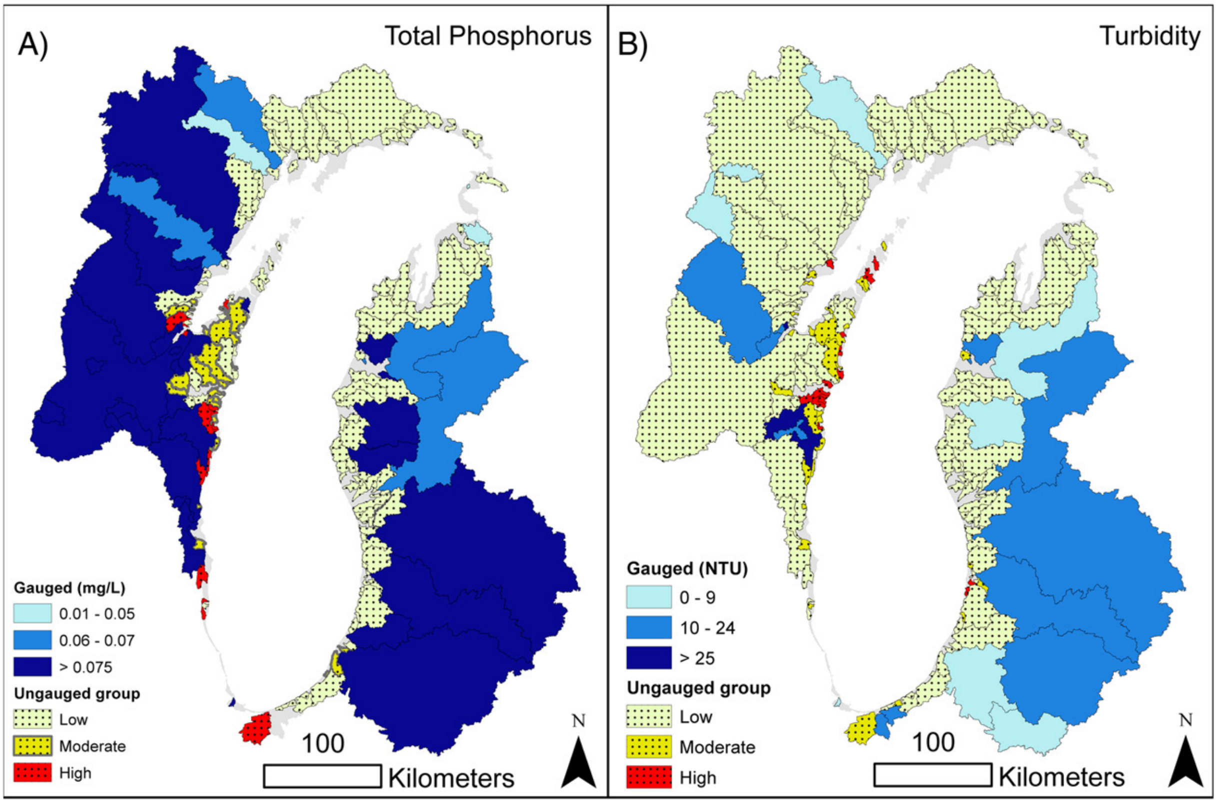

Fig. 5. Modeled spring runoff total phosphorus (mg/L) and turbidity (NTU) for watersheds with observed values (gauged) and based on landscape variables only (ungauged) for Lake Michigan. Gray areas are the portions of the basin not modeled.

forest disturbance and turbidity, particularly the spatial orientation and proximity of forest disturbance to streams and water quality stations (Peterson et al., 2011).

The conversion of forest land to other land uses can have profound impacts on water quality in streams and other water bodies. Forest

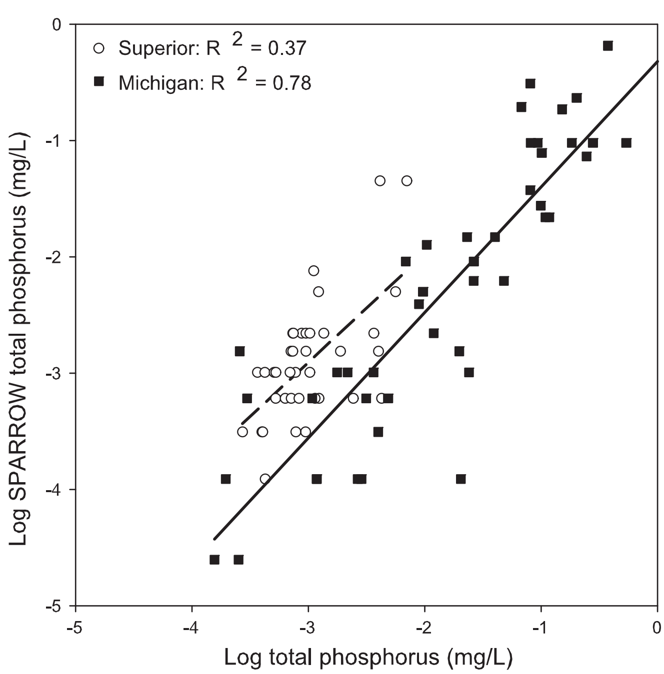

Fig. 6. Natural log-transformed total phosphorus estimates for gauged watersheds and SPARROW model estimates for Lake Superior (open circles) and Lake Michigan (black squares). Lines represent the linear regression for Lake Superior (dashed) and Lake Michigan (solid) and associated R^2 values in the upper left.

disturbance is associated with short-term increases in stream discharge (Stednick, 1996), along with increases in phosphorus (Meyer and Likens, 1979) and suspended sediment (Martin and Hornbeck, 1994). If the forest disturbance is short term (~5 years), followed by a return to forest, then water quality may only be disturbed for only a short time (Martin and Pierce, 1980; Thornton et al., 2000). On the other hand, if the forest is permanently transformed into a different land use (e.g., urban), then the changes in water quality may be more profound and long-lasting associated with the new land use (Allan, 2004). Only one of the models identified an older disturbance interval (1984–1999), so we were not able to identify long-term effects on water quality from forest disturbance that occurred more than five to ten years in the past, which is consistent with the short-term (2–5 years) disturbance in water quality that has been reported elsewhere (Thornton et al., 2000). When older disturbance was an important variable in the model, it was negatively correlated with TP concentration, so areas with higher proportions of older forest disturbance had lower TP. There were larger areas of older disturbance found in watersheds when there was also higher overall forest (e.g., northern half of the Lake Michigan basin). By overlaying the areas of older forest disturbance over recent land cover (NLCD), we were able to determine that old forest disturbance was serving as an indicator of low landscape development because those areas with older forest disturbance remained undeveloped. The Lake Michigan TP model also contained watershed storage, which was the proportion of watershed covered with open water and wetlands, and was negatively related to TP concentration. Watershed storage was also higher in the northern half of the Lake Michigan basin and represents lands that were not available for development.

The landscape of the Great Lakes basin is in constant flux, with approximately 2.3% reductions in both agricultural and forested land during the period from 1992 to 2001, along with increases in the percentage of urban land (Wolter et al., 2006). The increases in urban cover were the amount of low intensity development

(+33.5%), high intensity development (+19.6%), and roads (+7.5%; Wolter et al., 2006). The pattern of increased urban land and decreased agriculture and forest lands is expected to continue into the future (2060; Wear, 2011). Although urban lands make up a small part of the overall landscape, they have a disproportionate influence on water, habitat, and biotic quality (Paul and Meyer, 2001). The majority of the agricultural land that changed in the Great Lakes basin was to developed land, while the forest was split between changing to development (a permanent change) and early successional vegetation (temporary change leading to reforested; Wolter et al., 2006). Estimated nutrient loading from agricultural and urban land is estimated to be approximately 11 and 14 times, respectively, higher than forest (Wickham et al., 2002), although our models were able to identify forest coverage and disturbance data as a useful predictors of water quality degradation in the western Great Lake watersheds. Although water quality appears to rapidly return to less altered conditions following a disturbance, that may not be the case for the biotic communities where legacy effects have long-term influences even after the landscape has reverted to a more natural state (Harding et al., 1998). Future research is needed to investigate the relationship between biotic communities in streams and coastal wetlands with forest disturbance in the Great Lakes basin.

We provide managers with models to be used for the water quality-based ranking of watersheds within the Lake Superior and Lake Michigan basins using watershed-scale landscape information. Considering the more developed nature of the Lake Michigan basin compared to Lake Superior, we were surprised to find that field observations of NTU were higher for the Lake Superior watersheds. The difference in NTU between the lakes was not evident when a longer time period (2000–2009) for the spring melt period is considered, thus it appears that the higher NTU in Lake Superior was only an artifact of the time period of the data we used in the model. It should also be noted that because the watersheds in Lake Superior were smaller than in Lake Michigan, and watershed size is proportional to stream discharge, the total load being delivered to the nearshore zone would be higher in Lake Michigan, even if the measured concentrations in the tributaries were similar. Because these statistical models were based solely on the available water quality data within each Lake, we do not recommend comparing the predicted values between lakes, although it is reasonable to make comparisons of the predictors that were important in the models. Mechanistic models (e.g., SWAT) have a different relationship with field observations of water quality; watershed features are parameterized to estimate water quality without using observed water quality values, instead of using observed values for model calibration and post-hoc validation (Bosch, 2008).

Within the Lake Superior model, we were able to use the model predictions to identify the easily erodible Lake Superior Clay Plain (e.g., Nemadji River) in the southwestern Lake Superior watersheds, which contribute to higher concentrations of suspended sediment (Detenbeck et al., 2004; Shy and Wagner, 2007). On a watershed scale in the Nemadji River, forestry practices may have significant influence on sediment transport (Shy and Wagner, 2007). Reduced water clarity was more common in Lake Superior streams than elevated phosphorus, which may be linked to the attenuation of total phosphorus by fine clays (Bahnick et al., 1978; Fitzpatrick et al., 1999). This reduction in phosphorus may be observed in the tributaries but the nearshore waters may be impacted by the added sediment, in addition to the potential release of phosphorus from the clays (Boström et al., 1988; Steinman et al., 2006). The model had the opportunity to select an ecoregion that described the distinctive clay soil type in the southwestern portion of the basin, but ecoregion did not explain more variation than the current model for TP or NTU. This is an example of the utility of our models to identify turbidity problem areas where management actions are needed.

We compared our model with a TP loading model for the entire U.S. Great Lakes basin (Robertson and Saad, 2011). Both models utilized landscape-scale predictors, but our models also added forest-based predictors. The Great Lakes SPARROW model relates observed TP to potential sources in the watersheds, such as point sources, agriculture (confined manure, unconfined manure, and farm fertilizers), urban areas, and forested (including wetland) areas. We demonstrated that the general findings of the SPARROW model and our study are similar. Robertson and Saad (2011) found that the major source of TP in the Lake Superior basin was from forested land, while they found agriculture, urban, and point sources contributed most in the Lake Michigan basin. We found that persisting forest, disturbed forest 2000–2009, and agriculture were important variables for predicting TP in the Lake Superior basin, while ecoregion, disturbed forest 1984–1999, watershed storage, and urban land were significant variables in the Lake Michigan model. Our models showed that agriculture had a very pronounced effect on water quality in the Lake Superior basin, while there was a more complex relationship between TP and watershed factors in the Lake Michigan basin. In comparison to the SPARROW model, a strength of our model approach is that it allows for predictions directly related to forest management for TP and NTU, which can be targeted for work in the watershed to improve water quality in the tributaries and nearshore areas. Our model also utilizes higher resolution landscape data (i.e., 30 m pixels for VCT and NLCD), compared to the county scale extrapolations for agriculture in SPARROW (Smith et al., 1997). Our model is also more straightforward when considering future changes in landscape. We used proportions of land cover classes in our models, so these can be easily adjusted to simulate future scenarios, while SPARROW mixes total load from point sources and agriculture with the total area of forest and urban land use. The time period considered by the SPARROW model is standardized to represent a model year of 2002 and predicted annual total loads, while our model specifically relates to a more recent time period. Additionally, our models have a seasonal specificity (i.e., spring-runoff water quality) that may aid in planning for restoration because restoration plans can be customized to maximize efforts targeting the most important landscape factors. Because a high percentage of the total annual load occurs during the high runoff period in the spring, there was agreement between the two models about the relative condition of watersheds. Landscape data need to be generalized and aggregated to the watershed-scale to produce a model capable of making predictions of water quality. Our models and the Great Lakes SPARROW model use different predictors to describe the landscape, which results in different strengths and weaknesses for each modeling approach, but ultimately they are in agreement in the relative condition of watersheds. We suggest that both models be consulted when planning watershed management activities to utilize the strengths of each model and to most effectively use restoration funds.

Conclusions

We found that in the Lake Superior watershed, percentage agriculture was the most influential predictor, closely followed by forest disturbance, of TP concentrations, while forest disturbance was the primary factor, with agriculture also an important factor, correlated with increases in NTU. In the Lake Michigan watershed, concentrations of TP were correlated with the percentage of urban land, but decreased with old forest disturbance (1984–1999) and watershed storage. Forest disturbance and the relative abundance of softwood forest types were important predictors of turbidity in the Lake Michigan basin. Our model results for TP were consistent with a recent SPARROW model for the Great Lakes, but have the added prediction of turbidity. Our models compliment the SPARROW model by providing greater understanding of the role of forest and forest disturbance on TP in Lake Superior and Lake Michigan tributaries.

Our models can be used to predict the impacts of future management actions or multiple management scenarios. This will be especially true for the heavily forested Lake Superior and northern Lake Michigan areas, where our models will be directly useful in predicting water quality using forest indicators. The models can also be used to predict the expected water quality in a watershed of interest, and to estimate the expected change in water quality under alterative landscape configurations (e.g., urban development of watershed, large-scale disturbance of forest). In future work, we will refine the models to identify areas within larger watersheds and to include the spatial configuration of lands (e.g., buffers) to predict the water quality of Great Lakes tributaries.

Acknowledgments

Funding for this research was provided by the U.S. Environmental Protection Agency through the Great Lakes Restoration Initiative. The USEPA was not involved in the design, analysis, or writing of this manuscript. Valuable comments on earlier drafts were provided by R. Kolka, B. Tavernia, J. Stanovick, E. Rutherford, and the anonymous reviewers. The mention of trade names does not imply an official endorsement of the product.

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