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Forecasting cyanobacteria dominance in Canadian temperate lakes

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ABSTRACT

Predictive models based on broad scale, spatial surveys typically identify nutrients and climate as the most important predictors of cyanobacteria abundance; however these models generally have low predictive power because at smaller geographic scales numerous other factors may be equally or more important. At the lake level, for example, the ability to forecast cyanobacteria dominance is of tremendous value to lake managers as they can use such models to communicate exposure risks associated with recreational and drinking water use, and possible exposure to algal toxins, in advance of bloom occurrence. We used detailed algal, limnological and meteorological data from two temperate lakes in south-central Ontario, Canada to determine the factors that are closely linked to cyanobacteria dominance, and to develop easy to use models to forecast cyanobacteria biovolume. For Brandy Lake (BL), the strongest and most parsimonious model for forecasting % cyanobacteria biovolume (% CB) included water column stability, hypolimnetic TP, and % cyanobacteria biovolume two weeks prior. For Three Mile Lake (TML), the best model for forecasting % CB included water column stability, hypolimnetic TP concentration, and 7-d mean wind speed. The models for forecasting % CB in BL and TML are fundamentally different in their lag periods (BL = lag 1 model and TML = lag 2 model) and in some predictor variables despite the close proximity of the study lakes. We speculate that three main factors (nutrient concentrations, water transparency and lake morphometry) may have contributed to differences in the models developed, and may account for variation observed in models derived from large spatial surveys. Our results illustrate that while forecast models can be developed to determine when cyanobacteria will dominate within two temperate lakes, the models require detailed, lake-specific calibration to be effective as risk-management tools.

1. Introduction

The occurrence, frequency, magnitude and duration of cyanobacteria blooms in freshwater lakes is on the rise globally as anthropogenic activities continue to change our climate and increase nutrient concentrations (O'Neil et al., 2012; Paerl et al., 2011). Identification of factors that favour the development of cyanobacteria blooms in lakes is of vital importance for the effective management of our limited freshwater resources. Numerous limnological factors have been linked to the dominance of cyanobacteria and development of blooms in freshwater systems, including: (i) elevated nutrient concentrations, especially high phosphorus (P) (Schindler et al., 2008) and altered nitrogen to phosphorus (N:P) ratios (Posch et al., 2012; Schindler, 1977); (ii) low CO_2 or high pH (Shapiro, 1990); (iii) greater water column stability and algal buoyancy control (Paerl, 1988; Soranno, 1997); (iv) low underwater light (Havens et al., 1998); (v) anoxia and availability of ferrous iron (Molot et al., 2010, 2014) and (vi) top down processes related to the grazing activity of higher level organisms (DeMott et al., 1991; Rollwagen-Bollens et al., 2013).

Additionally, recent evidence has shown that blooms may be enhanced under specific meteorological conditions, such as high water temperature correlated to high air temperatures (Kosten et al., 2012; Paerl and Huisman, 2008; Taranu et al., 2012), low precipitation (Reichwaldt and Ghadouani, 2012; Romo et al., 2013), elevated solar irradiance (Zhang et al., 2012) and reduced wind speeds (Cao et al., 2006; Kanoshina et al., 2003). Among these

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factors, nutrient enrichment in particular has been associated with increases in algal biomass worldwide (Heisler et al., 2008). However, it is expected that climatic change will amplify bloom formation by increasing the geographical extent and frequency of blooms, lowering critical nutrient thresholds, and extending the seasonal duration of blooms within lakes (Johnk et al., 2008; Paerl and Huisman, 2009; Persaud et al., 2014).

Modelling cyanobacteria abundance and bloom occurrence is complex and challenging because they are affected by numerous interacting factors. For example, several studies have modelled cyanobacteria blooms in coastal systems (e.g. Wong et al., 2007), and large well studied freshwater lakes such Lake Taihu in China and Lake Windmere in the UK (e.g. Elliot, 2012; Zhang et al., 2012), but few models exist for small freshwater lakes that are common to many temperate lake districts (e.g. Elliot and Defew, 2012). In the past, predictive models based on broad, spatial surveys of numerous lakes have typically identified nutrient concentrations as the most important predictors of cyanobacteria abundance (e.g. Downing et al., 2001). More recently, however, research has indicated that both climatic variables, and limnological variables related to climate (e.g. surface water temperature), are also important predictors (Beaulieu et al., 2013; Kosten et al., 2012), and should therefore be taken into account when developing predictive and forecast models. This may be of particular importance when examining changes within lakes over time, where inter-annual differences in bloom intensity, duration, and phenology may be strongly influenced by meteorological conditions (Persaud et al., 2014). Furthermore, broad, landscape models typically have low predictive power (eg. Beaulieu et al. (2013); Downing et al. (2001); Taranu et al. (2012)) as they cannot account for small scale lake-specific parameters which may be instrumental in driving cyanobacteria dynamics.

The ability to forecast cyanobacteria dominance and bloom occurrence would be of tremendous value to lake managers. Forecast models are fundamentally different from simple predictive models in that they are based on dynamic relationships between cyanobacteria abundance, and limnological and environmental parameters over a time dimension. With such models, managers would be able to communicate exposure risks associated with recreational and drinking water use, as well as possible exposure to algal toxins, in advance of bloom occurrence. Forecast models would also be invaluable as an educational tool, providing knowledge to lake users and the general public regarding possible reasons for inter-annual differences in bloom intensity and duration, and providing clear guidance on management options for lakes experiencing blooms.

With over 2000 freshwater lakes within the Muskoka River Watershed of south-central Ontario, Canada, the Muskoka region is a focal point for tourism in Ontario and premier destination for recreational activities year round. Among the lakes in this region there are a few that experience cyanobacteria blooms on a recurring basis during the ice-free season. The factors driving cyanobacteria blooms in these temperate lakes are currently unknown. Therefore, we used algal data and numerous limnological and meteorological parameters to determine the factors that are closely linked to cyanobacteria dominance, and developed models to forecast cyanobacteria biovolume and possible bloom occurrence. Our primary goal is to develop forecast models that can be applied as a tool by resource managers to forecast bloom development, up to a month in advance. We are particularly interested in developing models that are easy to use by land managers, and assessing the differences and similarities between lake-specific models considering that the two lakes are in close proximity within the landscape.

2. Method

2.1. Study lakes

Brandy Lake (BL; 45° 06′ N, 79° 31′ W) and Three Mile Lake (TML; 45° 10′ N; 79° 27′ W) are moderately-sized, softwater lakes located 19 km apart in the Muskoka region of Ontario (Fig. 1). The watersheds of these lakes consist primarily of glacial deposits of sand, silt and clay with some organic deposits over granitic bedrock. Climatically, mean annual temperature and total precipitation for these lakes in the Muskoka region between the years 2000–2012 were 5.44 ± 0.78 °C and 1172 ± 121 mm, respectively (Environment Canada, http://www.cccma.ec.gc.ca/hccd/).

The two study lakes are different in their morphometric, chemical and physical characteristics (Table 1). Brandy Lake is much smaller, has a larger drainage ratio and faster flushing rate compared to mutli-basin TML (Table 1). BL can be classified as borderline eutrophic with epilimnetic spring total phosphorus (TP) and total nitrogen (TN) concentrations of 32.6 ± 9.80 $\mu g\ L^{-1}$ (mean ± SD) and 598 ± 67.5 $\mu g\ L^{-1}$ over the three years of study (as indicated in Table 1). BL has a relatively large (39.9 km^2) and wetland-dominated watershed. The watershed contains ~15% of productive wetlands and 78% of exposed bedrock (Ontario Ministry of Environment, 2006). Nutrient inputs are primarily from natural sources (due to its large drainage ratio), with an estimated 66% of the nutrients transported from the watershed into the lake originating from the wetlands (Ontario Ministry of Environment, 2006).

Three Mile Lake is classified as mesotrophic with spring total phosphorus and nitrogen concentrations of 13.8 ± 2.10 $\mu g\ L^{-1}$ and 467 ± 9.45 $\mu g\ L^{-1}$, respectively, over the three years. The watershed of TML is atypical within the Muskoka region as it supports a comparatively large agricultural community (8% of the watershed area) because pockets of the basin contain deeper soils that are more fertile compared to nearby locations. Paleoecological data suggest that deforestation was a major contributor to nutrient input into TML in the 1800s and early 1900s, however recent TP concentrations are lower than the historical peak as afforestation has occurred (Roland Hall, Department of Biology, University of Waterloo, unpublished). For this study we focussed on Hammell's Bay, the deepest (12 m) and only dimictic basin of TML. The hypolimnia of both Hammell's Bay and BL become anoxic seasonally, with dissolved oxygen concentrations less than 1 $mg\ L^{-1}$ by midsummer.

2.2. Phytoplankton

Algal samples were collected on a biweekly and monthly basis in each lake during the ice-free period over three years. In TML the samples were collected from the deepest point in Hammell's Bay in 2006, 2007 and 2012. In BL samples were collected from the deepest location of the main basin in 2002, 2003 and 2012. Water samples were collected as unfiltered, volume-weighted, euphotic zone composites (approximated as 2 × Secchi depth) using a polyvinyl chloride (PVC) pump-and-hose system. Collected samples were fixed with 1 mL Lugol's iodine solution in the field and stored in the laboratory until enumeration.

Using an inverted microscope and Utermöhl counting chambers, algal samples were counted by the Algal Taxonomy Unit Laboratory, Ontario Ministry of the Environment (Toronto, Ontario). Subsamples were preserved with two drops of 37% formalin and concentrated to 25 mL following settling. A minimum of 300 pieces (single cells or colonies) were counted and identified mainly to the genus level, and results were expressed as biovolume. Estimates of cell volumes for each taxon were obtained by measuring the dimensions of 30–50 cells and application of the geometric formula