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Development of predictive models for geosmin-related taste and odor in Kansas, USA, drinking water reservoirs

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ABSTRACT

The presence of taste and odor compounds can greatly reduce the quality of drinking water supplies. Because the monetary costs associated with the removal of these compounds can be high, it is impractical for most facilities to continuously treat their raw water. Instead, new tools are needed to help predict when taste and odor events may be most likely to occur. Water quality data were collected between June and October in 2006–2007 from five Kansas (USA) reservoirs in order to develop predictive models for geosmin, a major taste and odor compound; two of these reservoirs were also sampled during specific taste and odor events in December 2006 and January 2007. Lake trophic state alone was not a good predictor of geosmin concentrations as the highest average geosmin concentration was observed in the reservoir with the lowest nutrient and chlorophyll *a* concentrations. In addition, taste and odor events were not confined to summer months; elevated geosmin concentrations were observed in several reservoirs during the winter. Growth limitation by inorganic phosphorus appeared to be the primary determinant of geosmin production by algal cells in these reservoirs.

1. Introduction

Periodic taste and odor events influence the quality of drinking water in lakes and reservoirs throughout the world (e.g., Watson, 2003, 2004; Watson et al., 2008). However, the high costs of treatment with powdered activated charcoal or ozone make it impractical for most facilities to continuously treat their incoming raw water (Watson et al., 2007). Predictive tools thus are needed to determine when taste and odor events are most likely to occur; such tools would potentially allow treatment plant managers to initiate water treatment before major customer complaints occur.

One potential approach to managing taste and odor events would be to measure lake water concentrations of taste and odor-related compounds on a regular basis. Humans can detect geosmin (4,8a-dimethyldecalin-4a-ol), a common taste and odor compound, at extremely low concentrations. As a result, there is often only a short time between the appearance of geosmin in a water supply reservoir and the subsequent onset of complaints from drinking water customers

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(Taylor et al., 2006). A continuous, odor detection-based geosmin surveillance program could in principle be used to determine in advance whether to treat (e.g. geosmin detected) or not to treat (e.g. geosmin not detected) the raw incoming source water. However, the subjective human detection threshold for geosmin is very broad, and unfortunately can vary significantly from individual to individual as well as from date to date (see Methods). In addition, objective chemical measurements of geosmin require sophisticated technical training and special equipment, can be very expensive, and are not very rapid; completed chemical test results thus might not become available before large volumes of objectionable water enter the plant's drinking water distribution system.

Alternatively, it is possible that objectionable taste and odor events may be predictable from key water quality variables that are strongly correlated with geosmin concentrations, but are simpler and more cost-effective to measure (Table 1). Although a number of microorganisms can produce volatile organic compounds that affect the taste and smell of drinking water, several taxa of cyanobacteria (blue-green algae) frequently produce two key odor compounds, geosmin and 2-MIB, in aquatic environments where photosynthetic growth is possible (Jüttner and Watson, 2007). Fig. 1, for example, demonstrates a clear relationship between cyanobacterial biomass and taste and odor problems in Saginaw Bay (Lake Huron, USA). In water bodies where cyanobacterial blooms are common, it is therefore possible that cyanobacterial detection systems (Izydorczyk et al., 2005; Gregor et al., 2007), empirical models for cyanobacterial biomass (e.g., Downing et al., 1999), and/or water quality variables closely related to geosmin production (e.g. Davies et al., 2004; Sugiura et al., 2004) could be used to predict the likelihood of unacceptable taste and odor events. The environmental factors known to favor nuisance blooms of cyanobacteria and thus presumably geosmin include nutrient concentrations and ratios (Downing et al., 1999; Smith and Bennett, 1999; Smith, 2003), water clarity (Havens et al., 1998), water temperature and pH (Shapiro, 1990), and food web structure (Elser, 1999; Hunt et al., 2003).

The purpose of this research was to develop a series of empirical models for predicting geosmin concentrations using water quality variables measured in five Kansas (USA) reservoirs. In particular, we sought to compare the predictive power of cross-sectional reservoir models developed using data pooled from all five reservoirs, to the predictive power of models developed for individual reservoirs. In addition, we sought to identify key environmental variables that led to high levels of cellular geosmin production in these waters.

2. Methods

2.1. *Reservoir sampling and data collection*

Five Kansas (USA) drinking water reservoirs were selected to develop predictive taste and odor models: Big Hill, Cheney, Clinton, Gardner, and Marion. These reservoirs were selected to represent a range of water quality conditions and reservoir sizes in Kansas, and each has exhibited taste and odor events in the past (e.g. Smith et al., 2002; Wang et al., 2005; Ed Carney, Kansas Department of Health and Environment, personal communication). Each reservoir was sampled at roughly monthly intervals from June to October 2006; Big Hill and Clinton were also sampled in the winter of December 2006 and January 2007 during recognized taste and odor events.

A diverse group of chemical, physical, and biological variables were measured during each sampling event (Table 2). Water samples were collected from three different locations within each reservoir in order to capture possible spatial variability: one station in the riverine zone, one in the transition zone, and one in the lacustrine zone. When a given reservoir had more than one tributary, we sampled the tributary that was associated with greatest discharge. At each sampling site, *in situ* measurements of dissolved oxygen, turbidity, specific conductivity, pH, and water temperature were obtained with a Horiba field water quality checker at a depth of 1.5 m below the surface. A Secchi disk was used to measure transparency.

Two 1-L water samples were collected at each sampling site at a discrete depth of 1.5 m below the surface using a VanDorn sampler and returned to the Kansas Biological Survey's Ecotoxicology Laboratory, and stored in opaque Nalgene bottles at 4 °C. One of these water samples was used for analyses of total nitrogen (TN, $\mu g\,L^{-1}$), total phosphorus (TP, $\mu g\,L^{-1}$), and chlorophyll *a* (CHL, $\mu g\,L^{-1}$), while the other was used for the analysis of geosmin concentrations. Nutrient concentrations were determined colorimetrically (Cleceri et al., 2005) with a Lachat Model 4200 analyzer. Total nitrogen and total phosphorus concentrations were determined using the automated colorimetric procedures after persulfate digestion of unfiltered samples (Ebina et al., 1983). Samples for dissolved inorganic nutrients (NO_3-N, NH_4-N, and PO_4-P, $\mu g\,L^{-1}$) were filtered through ion chromatography Acrodisc filters (0.45 μm; Gelman Science) before analysis. All nutrient analyses were performed within 24 h of sample collection.

Chlorophyll *a* concentrations were determined using seston samples collected onto Whatman GF/F glass fiber filters.

Table 1 – Examples of previously published models that used water quality variables to predict geosmin concentrations in drinking water supplies.

Model	r^2 or R^2	Source waterbody	References
$\log(\text{GEOS}) = 1.07 \log(\text{TURB}_{\text{FNU}}) - 0.009\ (\text{SC}) + 7.23$	0.71	Cheney Reservoir, Kansas, USA	Christensen et al., (2006)
$\text{GEOS} = 0.412\ (\text{CHL}) - 1.08$	0.72	Cheney Reservoir, Kansas, USA	Smith et al., (2002)
$\text{GEOS} = 1.08\ (\text{SD}) - 0.064\ (\text{SC}) + 0.24\ (\text{TURB}_{\text{NTU}}) + 31.04$	0.70	Olathe Reservoir, Kansas, USA	Mau et al., (2004)
$\log(\text{GEOS}) = -0.624 - 1.092\ (\text{TP}) + 0.153\ (\text{COD}) + 0.149\ (\text{DO})$	0.70	Lake Kasumigaura, south-east Japan	Sugiura et al., (2004)

CHL = chlorophyll *a*; COD = chemical oxygen demand; DO = dissolved oxygen; GEOS = geosmin; SC = specific conductance; SD = Secchi Disk; TURB_{FNU} = tubidity in formazin Nephelometric Units; TP = total phosphorus; TURB_{NTU} = turbidity in Nephelometric Turbidity Unit.

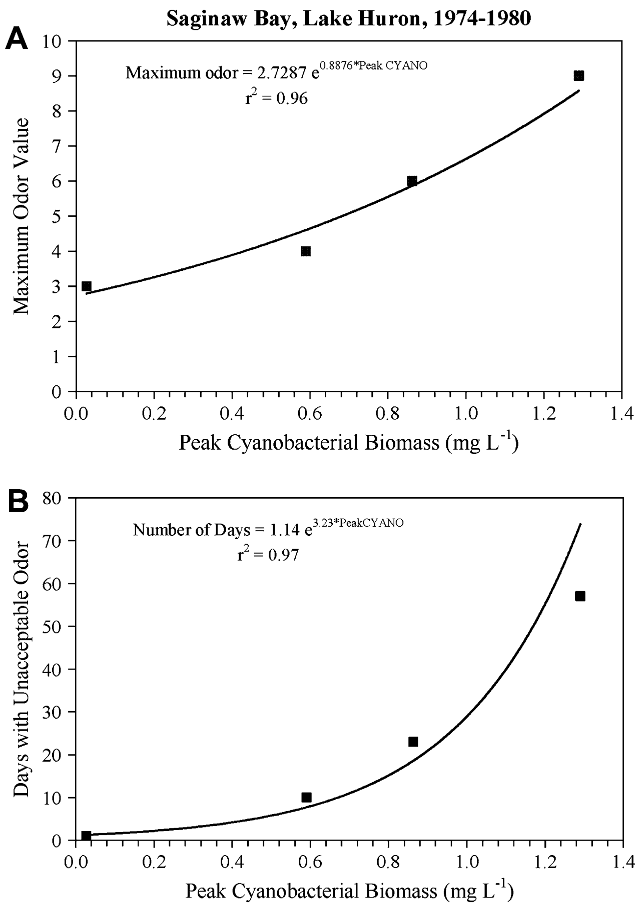

Fig. 1 – Cyanobacteria appear to have been primarily responsible for objectionable taste and odor problems and increased treatment costs in the Saginaw-Midland water supply system (Saginaw Bay, Lake Huron, USA) during 1974–1980. Changes in peak cyanobacterial biomass in Saginaw Bay were accompanied by strong changes in (A) the maximum threshold odor value; and (B) the number of days in which drinking water odor exceeded U.S.P.H.S. standards (threshold odor values > 3). Note: the y-axis values in (B) were rescaled (# of days + 1) to allow regression analysis of these data. Original data from Bierman et al. (1984).

These filters were frozen to rupture the algal cells, and chlorophyll *a* was then extracted in 90% basic (10% saturated $MgCO_3$) methanol for 20–24 h in the dark at 4 °C. Concentrations of chlorophyll *a*, corrected for phaeophytin *a*, were then determined by measuring the fluorescence of the sample with an Optical Technologies fluorometer before and after acidification (Cleceri et al., 2005).

Estimates of extracellular geosmin concentrations (GEOS; dissolved geosmin outside of the phytoplankton cells, ng L^{-1}) were determined on GF/F-filtered water samples at the Ecotoxicology Laboratory using the solid phase extraction technique of Pan (2002) followed by a gas chromatography and mass spectrometry (GC/MS). A 30-cm column (J&W Scientific) having a 0.25-mm internal diameter and a 0.25-μm HP-5MS film was used in the GC (HP5890). The MS (HP5971) was run in SIM mode for better detection. The detection limit for this technique was 5 ng L^{-1}, a value at the lower end of the range reported for subjective human testing (4–20 ng L^{-1}; see Davies et al., 2004 and references reported within). However, thresholds for the human detection of geosmin can vary over 3–4 orders of magnitude (Howgate, 2004), and thus human testing is far more variable and subjective than the analytical method used here. Furthermore, while there are a number of human sensory procedures in the literature, there is no recognized standard method (Howgate, 2004). Based on these reasons, we conclude that the objective analytical chemical methods used here are greatly preferable to human testers for generating the data needed for quantitative model development. Where required, we also calculated phytoplankton biomass-specific dissolved geosmin production (GEOSP, ng geosmin (μg chlorophyll a^{-1})) for each sampling date in order to identify key environmental variables that controlled geosmin production in these five reservoirs.

Water samples from each site were preserved in Lugol's solution for later microscopic analysis of phytoplankton community structure (Utermöhl, 1958; Cleceri et al., 2005). Five milliliters of each sample was settled in a 1.25 cm diameter settling chamber for 24 h and a total of 25–50 microscope fields were then chosen and counted at 400–1000× magnification. Four major taxa of cyanobacteria (*Aphanizomenon*, *Anabaena*, *Microcystis*, and *Oscillatoria*) were identified to genus, and their cellular biovolumes (μm^3 mL^{-1}) were determined by measuring the lengths of a subsample of cells from each genera and then applying appropriate geometric formula. We focused specifically on these four taxa because they tend to dominate cyanobacterial communities in Kansas reservoirs (deNoyelles, 2006), and because they are known to be closely associated with geosmin-related taste and odor events (Park et al., 2001; Jüttner and Watson, 2007). We also quantified the phytoplankton biovolume of all remaining algal species in each microscope field in a similar manner; these data were then used to calculate the relative biomass of cyanobacteria and the total algal biovolume in each sample.

2.2. *Model development*

Regression analysis was used to develop empirical models that relate analytically measured geosmin concentrations to the variables summarized in Table 2. All water quality data were checked for normality prior to model development; when these data did not meet the assumption of normality, $\log_{10}$ transformations were performed.

Two statistical methods were used to develop predictive models for geosmin. First, we used best-subsets regression, which provided the two 1-variable models with the highest coefficient of determination (r^2) values, the two 2-variable models with the highest R^2 values, and so forth. We also used stepwise regression, a procedure that adds candidate explanatory variables to the regression model one at a time ($P = 0.10$ to enter) if they significantly increase the model's predictive power; additional new variables are included until no further significant increase occurs in R^2, the coefficient of multiple determination (Sokal and Rohlf, 1995).

Table 2 – Summary of water quality variables collected from 5 Kansas (USA) reservoirs. These data represent average values from multiple samples in each reservoir over the duration of the study. Observed ranges are presented in parenthesis.

	Big Hill	Cheney	Clinton	Gardner	Marion
GEOS ($ng\,L^{-1}$)	11 (0–30)	7 (0–14)	11 (0–31)	1 (0–6)	5 (0–13)
pH	8.29 (7.48–8.82)	8.63 (8.23–8.87)	8.43 (7.76–8.88)	8.29 (7.6–9.1)	8.58 (8.20–8.90)
SC ($mS\,cm^{-1}$)	0.23 (0.20–0.26)	0.79 (0.70–0.95)	0.30 (0.27–0.35)	0.36 (0.29–0.44)	0.52 (0.46–0.59)
DO ($mg\,L^{-1}$)	8.54 (5.44–10.67)	9.10 (5.78–11.54)	9.60 (6.96–13.46)	7.94 (3.94–16.25)	7.92 (6.64–10.11)
TURB (NTU)	12 (5–19)	62 (19–180)	34 (8–90)	25 (9–52)	121 (34–528)
SD (cm)	142 (98–180)	49 (20–70)	69 (25–145)	78 (36–100)	42 (15–80)
TEMP (°C)	23.1 (6.6–30.0)	25.7 (19.6–32.4)	22.7 (4.3–28.6)	23.4 (14.3–30.6)	24.4 (18.4–28.0)
NO_2^--N ($\mu g\,L^{-1}$)	4.4 (0–10)	7.2 (0–40)	8.6 (0–30)	9.3 (0–40)	7.8 (0–40)
NO_3^--N ($\mu g\,L^{-1}$)	68.9 (0–270)	40.9 (0–130)	66.1 (0–170)	108.0 (0–980)	56.1 (0–300)
NH_3-N ($\mu g\,L^{-1}$)	35.1 (1.5–115.0)	27.1 (3.9–89.2)	21.2 (4.0–55.1)	67.7 (0.39–285.0)	40.5 (0–228)
TN ($\mu g\,L^{-1}$)	581 (456–810)	884 (720–1310)	655 (470–970)	791 (560–1900)	1336 (760–3420)
PO_4^{3-}-P ($\mu g\,L^{-1}$)	6.8 (0.7–21.9)	15.5 (3.6–26.1)	13.7 (2.9–21.7)	22.8 (2.0–127.0)	65.2 (31.1–118.0)
TP ($\mu g\,L^{-1}$)	23.4 (8.4–35.1)	85.2 (57.9–209.0)	61.0 (28.2–116.0)	72.9 (35.3–248.0)	206.7 (121.0–384.0)
TN/TP	29 (16.2–75.0)	11 (6.3–13.6)	12 (6.3–17.1)	12 (7.6–17.3)	7 (3.9–10.1)
CHL ($\mu g\,L^{-1}$)	12.7 (6.1–22.4)	27.2 (12.0–42.6)	21.3 (9.3–32.5)	25.6 (6.8–104.6)	51.1 (19.1–183.0)
APH ($\mu m^3\,mL^{-1}$)	285,694 (55,513–531,417)	26,705 (0–208,173)	26,614 (0–181,677)	0	0
MIC ($\mu m^3\,mL^{-1}$)	0	3529 (989–10,999)	147 (0–1112)	0	1634 (0–6180)
ANA ($\mu m^3\,mL^{-1}$)	40,356 (14,599–913,488)	418,624 (358,721–1,234,668)	221,470 (18,770–846,748)	148,309 (0–559,865)	504,828 (12,514–2,882,282)
OSC ($\mu m^3\,mL^{-1}$)	56,262 (1236–118,028)	193,440 (0–800,900)	5704 (0–20,907)	22,850 (0–91,148)	4691 (0–42,021)
TOTCYAN ($\mu m^3\,mL^{-1}$)	745,518 (238,349–1,324,786)	642,298 (62,568–1,594,690)	253,936 (22,941–1,028,427)	171,159 (9681–651,012)	511,154 12,514–2,883,147)
TOTALG ($\mu m^3\,mL^{-1}$)	972,052 (290,077–1,628,324)	1,161,668 (360,297–2,847,650)	724,044 (223,776–2,207,232	1,003,215 (160,029–3,002,917)	1,406,333 (159,710–3,944,295)

GEOS = geosmin; SC = specific conductance; DO = dissolved oxygen; TURB = turbidity; SD = Secchi Disk; TEMP = water temperature; TN = total nitrogen; TP = total phosphorus; CHL = chlorophyll *a*; APH = *Aphanizomenon* biovolume; MIC = *Microcystis* biovolume; ANA = *Anabaena* biovolume; OSC = *Oscillatoria* biovolume; TOTCYAN = total cyanobacterial biovolume; TOTALG = total algal biovolume.

Each of the regression procedures provided a number of significant models ($P \leq 0.05$); therefore, we used two primary considerations when selecting the "best" regression models for presentation below. First, we evaluated their r^2 or R^2 values, which provide measures of how much of the variation in geosmin concentrations was explained by the predictor variable(s) in a specific model. Only statistically significant models ($P \leq 0.05$) were selected for further consideration. Second, from a management perspective, we presented models that included variables that were relatively easy and inexpensive to collect relative to geosmin.

Both single-variable and multiple-variable models were developed for individual reservoirs; in addition, cross-sectional models were developed using all available data pooled from the five reservoirs. Model development was based solely upon samples having geosmin concentrations above our analytical detection limit of 5 ng L^{-1}; based upon graphical analyses of the entire data set, as well as the complex issues created by the use of non-detect values in statistical analyses (Helsel, 2004), all below-detection-limit geosmin samples were excluded from the model development.

3. Results

3.1. Water quality conditions

Average water quality conditions varied considerably in the five reservoirs (Table 2). In general, total nutrients, chlorophyll *a*, and turbidity were lowest in Big Hill and highest in Marion. Using the trophic state criteria presented in Smith et al. (1999), Big Hill was classified as mesotrophic; Cheney, Clinton, and Gardner were classified as eutrophic; and Marion was classified as hypereutrophic.

Cyanobacteria were present in the phytoplankton of each of the five reservoirs (Fig. 2). Algal communities in Big Hill (average relative biovolume over the course of the study = 75.3%) and Cheney (53.3%) exhibited the greatest dominance by cyanobacteria. *Aphanizomenon* and *Anabaena* were the dominant cyanobacterial taxa in these two reservoirs respectively. On average cyanobacteria accounted for less than 50% of the total algal biovolume in Clinton (30%), Gardner (21%), and Marion (27.5%). *Anabaena* was the dominant cyanobacterium observed in these three reservoirs (Fig. 2).

3.2. Geosmin data

Geosmin concentrations were below analytical detection limits (5 ng L^{-1}) in 87% of the samples that were collected from Gardner. In contrast, geosmin concentrations exceeded 5 ng L^{-1} in 67%, 89%, 86%, and 55% of the samples collected from Big Hill, Cheney, Clinton, and Marion reservoirs respectively.

Differences also were apparent in the temporal dynamics of geosmin in the 5 reservoirs (Fig. 3). In two of the reservoirs, Big Hill and Clinton, peak geosmin concentrations were observed in the month of December (Fig. 3). In contrast, the highest measured geosmin concentrations in Marion occurred during July and September, when dense algal blooms were observed on the surface of the reservoir. Much less temporal variation in geosmin was observed in Cheney and Gardner than in the other three reservoirs (Fig. 3); however, it is important to note that we did not sample Cheney, Gardner, and Marion in the winter so we do not know if they also experienced winter peaks in geosmin. Because of this bias in temporal sampling, we did not include temperature in the predictive models described below. However, the inclusion of data from these samples (minus temperature) did allow us to incorporate a greater temporal scale into the model development.

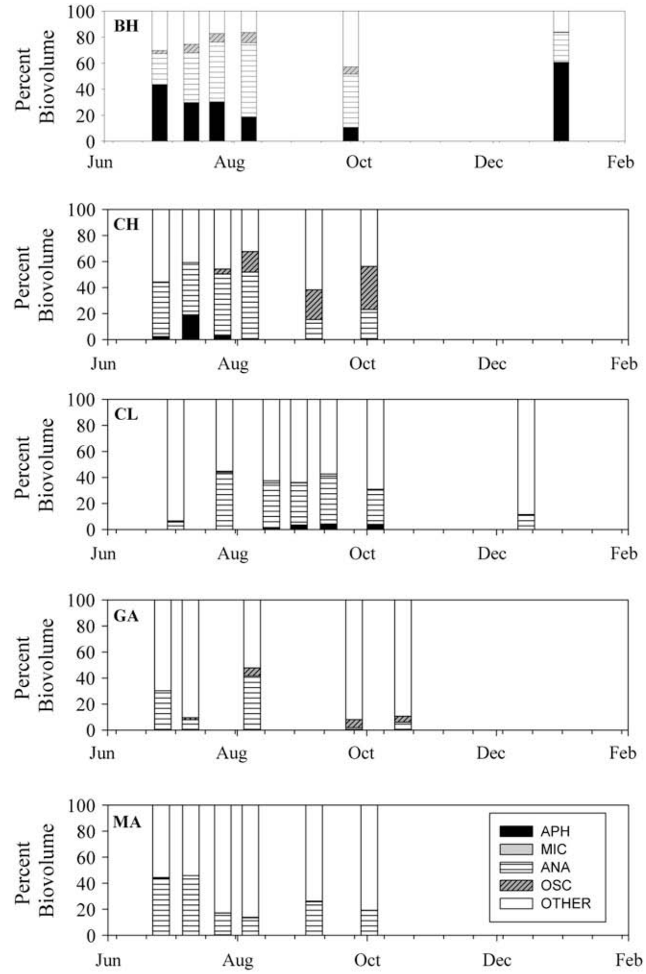

Fig. 2 – Average phytoplankton community composition (% by biovolume) in each of the five reservoirs over the course of the study. Data represent averages from the three samples collected on each sample date.

3.3. Model development

Initially, we developed empirical models for geosmin using several scenarios. First, models were developed individually for each of the three zones of a reservoir (lacustrine, transition, and riverine). However, models that included data from all three of the sites combined provided relatively similar predictive power as did the models that used data from each specific site individually (data not shown). Therefore, all of the spatial data from the three zones of

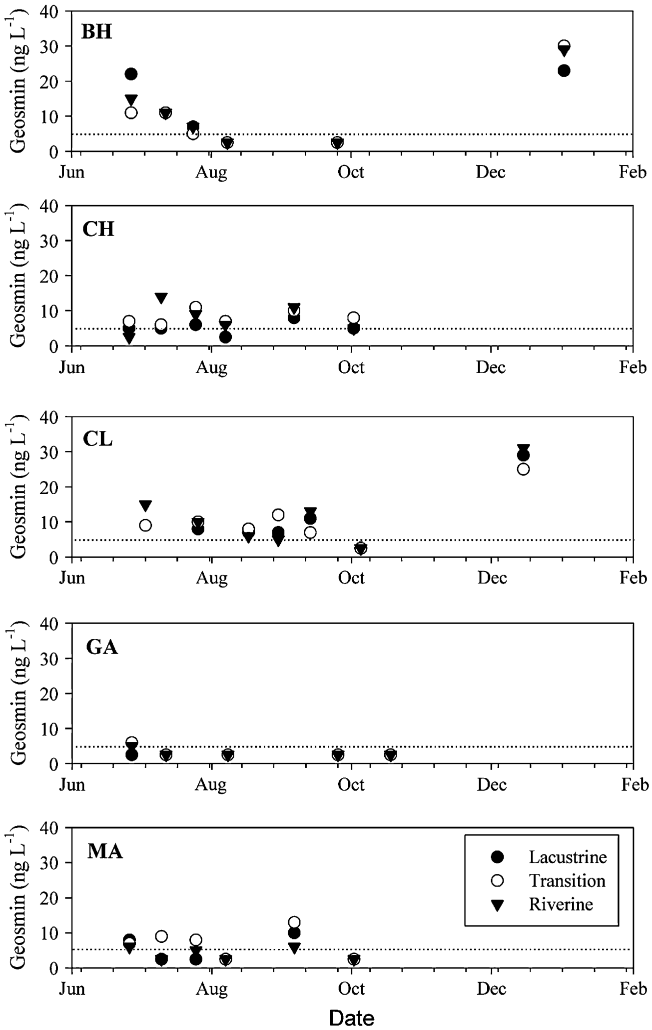

Fig. 3 – Temporal variation in geosmin concentrations in each of the five reservoirs over the course of the study. Note that samples with geosmin concentrations below the analytical detection limit (horizontal line) are represented on the graph as 2.5 ng L^{-1}. BG = Big Hill; CH = Cheney; CL = Clinton; GA = Gardner; MA = Marion.

each reservoir were pooled for use in model development. Also, individual reservoir models were not developed for Gardner because only one sample date had geosmin concentrations that were above our analytical detection limit of 5 ng L^{-1}.

3.3.1. *Cross-sectional models*

Two, one-variable cross-sectional models were developed that explained 24% and 25% (r^2 – the coefficient of determination) of the variation in geosmin concentrations (Fig. 4):

$$\log(\mathrm{GEOS}) = 0.20 - 0.42 \log(\mathrm{SD}),\ r^2 = 0.24,\ P < 0.001,\ n = 57 \quad (1)$$

$$\log(\mathrm{GEOS}) = 1.19 - 0.22 \log(\mathrm{PO_4\text{-}P}),\ r^2 = 0.25,\ P < 0.001,\ n = 57 \quad (2)$$

Two, two-variable cross-section models were developed that explained 34% and 35% (R^2 – the coefficient of multiple determination) of the variation in geosmin concentrations:

$$\log(\mathrm{GEOS}) = 1.1 + 2.67 \log(\mathrm{NO_3\text{-}N}) - 0.19 \log(\mathrm{PO_4\text{-}P}),\ R^2 = 0.34,\ P < 0.001,\ n = 57 \quad (3)$$

$$\log(\mathrm{GEOS}) = 2.03 - 0.18 \log(\mathrm{PO_4\text{-}P}) - 0.163 \log(\mathrm{ANA}),\ R^2 = 0.35,\ P < 0.001,\ n = 57 \quad (4)$$

3.3.2. *Individual reservoir models*

3.3.2.1. *Big Hill*. A number of highly significant one-variable models were developed for Big Hill that explained up to 89% of the variation in geosmin concentrations (Fig. 5). Two such models are presented below:

$$\mathrm{GEOS} = 69.48 - 8.32\ (\mathrm{CHL}) + 0.276\ (\mathrm{CHL})^2,\ R^2 = 0.87,\ P < 0.001,\ n = 12 \quad (5)$$

$$\mathrm{GEOS} = 34.29 - 0.00002\ (\mathrm{TOTALG}),\ r^2 = 0.89,\ P < 0.001,\ n = 12 \quad (6)$$

A two-variable model was developed for Big Hill that explained 94% of the variation in geosmin concentrations:

$$\mathrm{GEOS} = 39.0 - 0.609\ (\mathrm{TP}) - 0.00002\ (\mathrm{TOTCYAN}),\ R^2 = 0.94,\ P < 0.001,\ n = 12 \quad (7)$$

3.3.2.2. *Clinton*. Two, one-variable regression models were developed for Clinton that explained 36 and 61% of the variation in geosmin concentrations (Fig. 5):

$$\log(\mathrm{GEOS}) = 2.48 - 0.276 \log(\mathrm{TOTCYAN}),\ r^2 = 0.36,\ P = 0.009,\ n = 18 \quad (8)$$

$$\log(\mathrm{GEOS}) = 0.970 - 0.004\ (\mathrm{SD}) + 0.000054\ (\mathrm{SD})^2,\ R^2 = 0.61,\ P = 0.001,\ n = 18 \quad (9)$$

A three-variable model was developed for Clinton that explained 85% of the variation in geosmin concentrations:

$$\log(\mathrm{GEOS}) = -1.24 + 0.37\ \mathrm{pH} + 0.005\ \mathrm{SD} - 0.215 \log(\mathrm{TOTALG}),\ R^2 = 0.85,\ P < 0.001 \quad (10)$$

3.3.2.3. *Cheney*. We were unable to develop any significant regression models for predicting geosmin concentrations using the data collected from Cheney as part of the current study (all models $P > 0.05$).

3.3.2.4. *Marion*. A single-variable regression models were developed for Marion that explained 47 of the variation in geosmin (GEOS) concentrations (Fig. 5):

$$\mathrm{GEOS} = -8.76 + 2.11\ (\mathrm{DO}),\ r^2 = 0.47,\ P = 0.04,\ n = 9 \quad (11)$$

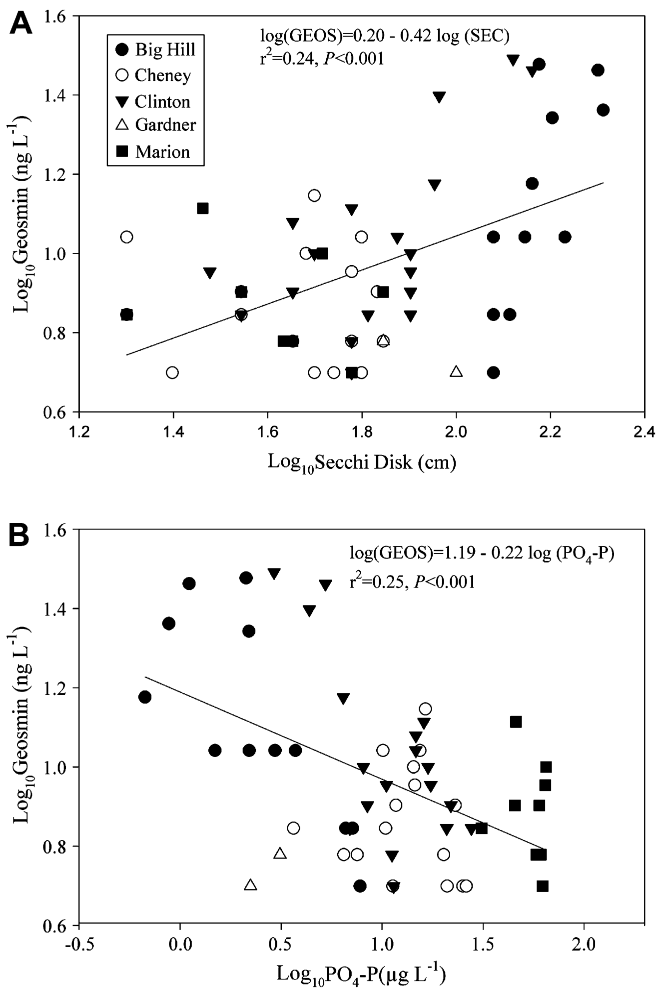

Fig. 4 – Significant regression relationships between (A) Secchi Disk (SD, cm) and geosmin (GEOS, ng L^{-1}) and (B) Dissolved inorganic phosphorus (PO_4-P, µg P L^{-1}) and geosmin (GEOS, ng L^{-1}) for the cross-sectional data set.

A three-variable model was developed for Marion that explained 93% of the variation in geosmin concentrations:

$$\mathrm{GEOS} = -9.93 + 3.02\ (\mathrm{DO}) + 9.33\ \log(\mathrm{CHL}) - 3.58\ \log(\mathrm{TOTALG}),\quad R^2 = 0.93,\ P = 0.002,\ n = 9 \tag{12}$$

4. Discussion

4.1. General trends in geosmin concentrations

While it is often assumed that eutrophic or hypereutrophic reservoirs are most vulnerable to taste and odor events, our results suggest that trophic state *per se* is not a strong predictor of geosmin in Kansas drinking water reservoirs. For example, Big Hill, which was classified as mesotrophic based on its nutrient and chlorophyll *a* concentrations, had the highest average geosmin concentrations of the five reservoirs (Table 2). In contrast, geosmin was rarely detected in Gardner, even though it was classified as eutrophic based on its nutrient and chlorophyll concentrations. Others have similarly pointed out that taste and odor events commonly occur in oligo-mesotrophic water supplies in other regions of the world (e.g. Watson et al., 2001; Watson, 2004).

Our results also suggest that taste and odor events are not confined to summer months in Kansas drinking water reservoirs (Fig. 3). Winter taste and odor events were observed in both Big Hill and Clinton. Additionally, we did not sample the other three reservoirs in the winter so we do not know if they also experienced winter geosmin events. Winter taste and odor events have been previously observed in Clinton Lake (e.g. Wang et al., 2005) and in other regions of the world (e.g. Watson et al., 2001; Jüttner and Watson, 2007). As such, we suggest that seasonal data be collected and be incorporated into future model development.

Finally, we were unable to identity consistent spatial patterns in geosmin production either between or within the reservoirs. There did not appear to be a specific reservoir zone in which geosmin concentrations were consistently higher than they were in the other reservoir zones (Fig. 3). For example, in some reservoirs (e.g. Big Hill and Clinton) geosmin concentrations were greatest in different zones during different seasons. In other reservoirs there was little spatial

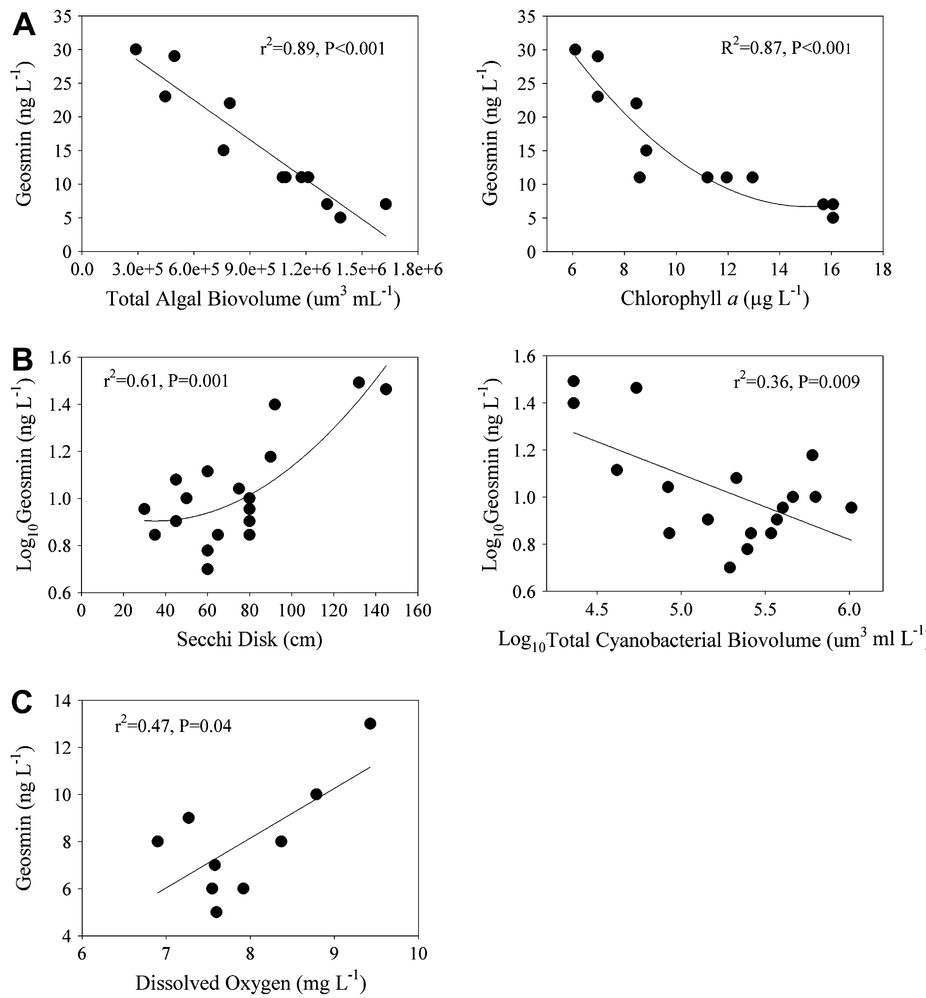

Fig. 5 – (A) Significant regression relationships between total algal biovolume and geosmin, and chlorophyll *a* and geosmin in Big Hill. (B) Significant regression relationships between Secchi Disk transparency and geosmin, and total cyanobacterial biovolume and geosmin in Clinton. (C) Significant regression relationships between dissolved oxygen and geosmin in Marion. See text for regression equations.

variability over the course of the study (e.g. Gardner and Cheney), while Marion was the only reservoir in which geosmin was consistently greatest in a specific reservoir zone (Fig. 3). Replicated sampling conducted over a greater spatial scale within individual reservoirs will help to determine if there are consistent spatial patterns in geosmin production that may be useful in the development of management strategies and predictive models.

4.2. *Predictive variables for dissolved geosmin (GEOS)*

Surprisingly, instantaneous measurements of cyanobacterial biovolume (either total biovolume or the biovolume of any of the individual taxa) were not a consistent predictor of dissolved geosmin in this study. Furthermore, in those models that did include cyanobacteria, cyanobacterial biovolume was *negatively* related to geosmin (Eqs. (4) and (7)). These results contrast with the data in Fig. 1, and with data presented by other investigators who have shown that geosmin is *positively* correlated with cyanobacterial biovolume (e.g. Sugiura et al., 2004; Jüttner and Watson, 2007). However, it can be difficult to detect relationships between the biomass of taste and odor producers and geosmin if it is not measured as both cell-bound (particulate) and dissolved (extracellular) fractions (Jüttner and Watson, 2007). Particulate geosmin can build up within individual cyanobacterial cells and then be released as dissolved geosmin depending on specific environmental conditions that affect cell degradation or as they are grazed by zooplankton (Jüttner and Watson, 2007; Satchwill et al., 2007). As such, relationships between cyanobacteria and geosmin may be more apparent if particulate geosmin is measured as well. Therefore, future research should assess relationships between both particulate and extracellular fractions of geosmin to determine which measurement is most useful in model development. Geosmin concentrations can also vary spatially within individual reservoirs (e.g. Davies et al., 2004; Jüttner and Watson, 2007), and our fixed sampling depth of 1.5 m might not have accurately captured geosmin concentrations and cyanobacterial biovolume. Moreover, because dissolved geosmin breaks down relatively slowly in the water column, the dynamics of geosmin may become disconnected from instantaneous measurements of algal biomass.

It is also important to note that pelagic cyanobacteria are not the only microorganisms that produce taste and odor compounds. Benthic cyanobacteria and periphyton (Watson and Ridal, 2004; Jüttner and Watson, 2007) and actinomycete bacteria from terrestrial sources (Sugiura and Nakano, 2000; Lanciotti et al., 2003; Nielsen et al., 2006; Jüttner and Watson, 2007) have also been shown to produce geosmin. Unfortunately, due to the financial and personnel constraints of the project it was not possible to assess all potential sources of geosmin. Therefore, it is unknown what role, if any, these additional taste and odor producers play, and future research is needed to determine how these additional organisms influence taste and odor events in Kansas drinking water reservoirs.

However, a number of additional water quality variables were identified as significant predictors of geosmin. Of these variables, several are relatively easy to collect and/or measure and could potentially be incorporated into early warning taste and odor control systems at individual water treatment facilities. For example, there was a positive relationship between Secchi Disk (SD) and geosmin in Clinton Lake (Eq. (9)). Elevated geosmin concentrations were always observed when Secchi Disk depths were greater than 80 cm in this reservoir (Fig. 5). Low Secchi Disk depths (<80 cm), however, would be much less effective in predicting taste and odor events in Clinton. The strong importance of light availability in the water column for geosmin production is not surprising: light energy provides the reducing power necessary for the photosynthetic fixation of dissolved inorganic carbon, which can then be routed into the cellular synthesis of this volatile alicyclic alcohol. Similarly, Halstvedt et al. (2008) reported strong positive effects of light availability on secondary compound production by field populations of cyanobacteria.

Interestingly, several of the previously developed models for predicting geosmin presented in Table 1 identified similar variables as the models presented here. For example, Secchi Disk was a significant predictor in a multiple-variable model for Olathe Lake, KS and dissolved oxygen was a significant predictor in a multiple-variable model for Lake Kasumigaura, Japan (Table 1). Comparisons of the models in Table 1 also indicate that specific conductance, although not included in any of our models, is an important predictor of geosmin that should be included in future analyses and model development. Surprisingly, turbidity was positively correlated with geosmin in a number of the previous models, whereas geosmin concentrations tended to increase in more transparent water (i.e. high Secchi Disks; Fig. 5) in Clinton. Therefore, additional research is needed to better understand the relationships between geosmin, turbidity (algal versus non-algal), and Secchi Disk.

Cheney was the only reservoir for which we were unable to identify any significant water quality predictors of geosmin. In contrast, previous studies were able to develop significant models for this reservoir, each of which identified different variables as predictors of geosmin concentrations (see Smith et al., 2002 and Christensen et al., 2006 in Table 1). It is important to point out that Smith et al. (2002) developed models using a larger data set, both in terms of spatial and temporal sampling; moreover, during model development they utilized seasonal mean values, rather than the instantaneous measurements analyzed here. Similarly, Christensen et al. (2006) developed models based on continuously collect data (30–60 min intervals). Therefore, the more intensive sampling schedules used in these previous studies may have allowed for a more complete examination of the factors affecting geosmin production in Cheney. Combined these results highlight the fact that relationships between geosmin and water quality variables can be highly variable over time even within individual reservoirs. Because of this strong potential for temporal variation in geosmin production we suggest that multiple year data sets be used in the development of future predictive models.

Perhaps most importantly, dissolved inorganic phosphate was also a significant predictor of geosmin in several models (Eqs. (2)–(4); Fig. 4). It was initially surprising that negative relationships were observed between geosmin and dissolved inorganic phosphate concentrations in the models, but such relationships have also been found in a Korean water supply reservoir (Park et al., 2001). It is possible that as phytoplankton biomass increased, the growth of these cells depleted the available PO_4-P, resulting in subsequent blooms and increases in geosmin concentrations (e.g. Wang et al., 1999; Park et al., 2001). Regardless of the mechanism, however, it is important to note that low concentrations of dissolved inorganic phosphorus may serve as an important indicator of taste and odor events in early warning systems, and the effects of phosphorus limitation are analyzed further below.

4.3. *Effects of phosphorus limitation on biomass-specific geosmin production*

As noted above, dissolved inorganic phosphorus concentrations (PO_4-P) were a significant predictor of geosmin in several regression models, but the sign of this effect was consistently *negative*. We explored this observation further by examining the effects of P-limitation on geosmin production in the five studied reservoirs.

Conditions of strong P-limitation should restrict cyanobacterial cell division, leading to high intracellular concentrations of the reduced organic carbon backbones that are needed for geosmin synthesis, and thus favoring high rates of cellular geosmin production and potential leakage into the water column. Given that the phytoplankton in all five Kansas reservoirs contained significant biomass of one or more species of cyanobacteria (Fig. 2), we tested this hypothesis using calculated values for instantaneous phytoplankton biomass-specific geosmin production (GEOSP, ng dissolved geosmin per μg chlorophyll *a*; see Methods section) in order to assess the degree to which geosmin production by the phytoplankton was dependent upon PO_4-P in these five reservoirs.

PO_4-P concentrations less than $10\,\mu g\ P\,L^{-1}$ are typically considered to be indicative of phosphorus limitation of phytoplankton growth (Sas, 1989), and as can be seen in Fig. 6A, there was a strong inverse relationship between GEOSP and PO_4-P under these conditions. In contrast, when P was inferred to be non-limiting (PO_4-P concentrations $>10\,\mu g\ P\,L^{-1}$), biomass-specific geosmin production values were consistently very low.

The putative effects of P-limitation on biomass-specific geosmin production are further underscored by a plot of GEOSP versus the TN:TP ratio, which can be used as an

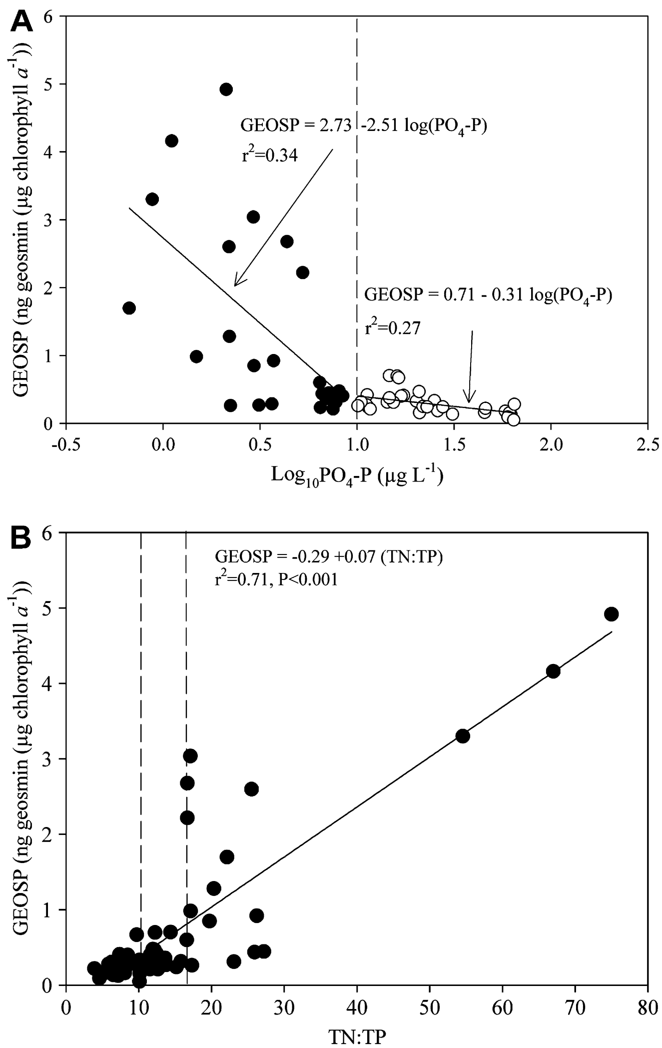

Fig. 6 – (A) Relationship between biomass-specific dissolved geosmin production (GEOSB, ng geosmin (μg chlorophyll a^{-1})) and concentrations of dissolved inorganic phosphorus (PO_4-P, μg P L^{-1}) in the five reservoirs. The vertical line indicates a concentration of 10 μg P L^{-1}. (B) Relationship between GEOSB and the total nitrogen:total phosphorus ratio (TN:TP, by mass) in the five reservoirs. The two vertical lines denote the empirical upper limit for nitrogen limitation (TN:TP = 10) and the empirical lower limit for phosphorus limitation (TN:TP = 17) suggested by Sakamoto (1966).

objective indicator of algal nutrient limitation status (Sakamoto, 1966; Smith et al., 1999). As can be seen in Fig. 6B, GEOSP values were consistently very low when nitrogen limitation was inferred (TN:TP < 10 by mass); increased under conditions of joint N- and P-limitation (10 < TN:TP < 17); and were maximal under P-limited conditions when nitrogen was in great abundance (TN:TP > 17). This response is broadly consistent with the results of Saadoun et al. (2001), in which the highest biomass-specific geosmin contents of laboratory-cultured *Anabaena* occurred at the highest supply rates of inorganic nitrogen, and Von Elert and Jüttner (1997), in which phosphorus limitation controlled the extracellular release of allelopathic compounds by *Trichormus doliolum*. The relationship shown in Fig. 6B is in sharp contrast with the N:P ratio hypothesis of cyanobacterial dominance (Smith, 1983), however, and additional research is needed to confirm this response pattern and its generality. In riverine systems dominated by benthic cyanobacteria, for example, conditions of nitrogen limitation were thought to trigger the release of geosmin from cyanobacterial mats (Sabater et al., 2003).

4.4. Model refinement and implementation

The cross-sectional models reported in this study explained only a relatively modest percentage ($R^2 = 0.24$–0.35) of the variation in measured geosmin concentrations pooled from multiple sampling sites and dates within each of five Kansas reservoirs. From a treatment perspective, these cross-sectional models likely do not provide sufficient explanatory power for plant operators to make cost-effective treatment decisions. In contrast, individual reservoir models (with the exception of Cheney) typically explained a greater percentage of variation in geosmin, suggesting that the dissolved concentrations of this taste and odor compound are strongly dependent upon local environmental factors that vary from system to system. As such, models for individual reservoirs may be required to effectively manage and predict taste and odor events using plant-monitored water quality variables. Alternatively, it is possible that models could be developed for groups or clusters of reservoirs that exhibit similar characteristics such as surface area, watershed land use/land cover, food web structure, and trophic state. However, more data from a greater variety of reservoirs will be needed to develop such individualized models.

While we have presented a generalized framework for predicting geosmin concentrations using water quality variables, it is important to stress that the presented models have not been tested and their accuracy in predicting actual taste and odor events is unknown. As such, there are several factors that should be considered when refining and implementing these and other models for use in taste and odor control. First, models should be chosen to include variables that are relatively easy and inexpensive to collect in order to encourage use by treatment personnel. Second, the data acquisition time must be rapid for the models to be effective at predicting taste and odor events in a time frame that allows for management decisions to be made before taste and odor events begin. Third, reservoir specific research is needed to determine the time frame within which samples need to be collected so that taste and odor events are detected in the early stages. Fourth, the model structure and data input process must be easy and user friendly for the models to be effectively incorporated into treatment schedules. Finally, it is unknown if conditions are similar between raw water samples obtained from treatment plants as the water begins treatment and samples obtained for the reservoir itself. Since the models presented here have been developed using reservoir samples, additional research is needed to determine if similar relationships exist between water quality variables and geosmin in raw water samples as well.

While much is known about the effects of eutrophication on aquatic ecosystems, many important research frontiers still remain (Smith and Schindler, 2009). Given the potential ecological and socioeconomic threats posed by noxious algal metabolite outbreaks, it is important to develop a multistep water quality management framework that combines broad-scale screening and nutrient management with system- and taxa-specific approaches (Watson et al., 2008). We hope that the results presented here will stimulate future research that will allow us to better predict the environmental conditions that result in objectionable taste and odor in our water supplies, and result in new tools that will assist water treatment operators in delivering the highest quality product possible to their customers.

5. Conclusions

- A series of predictive models were developed relating water quality variables to dissolved geosmin concentrations using data collected from five Kansas (USA) reservoirs. In general, models based upon data collected from individual systems tended to explain more of the observed variation in geosmin than did cross-sectional models constructed using a pooled data set from multiple reservoirs.
- Multiple year data sets may be necessary to incorporate temporal variation in geosmin concentrations within individual reservoirs.
- Trophic state alone was not a good predictor of geosmin concentrations: the highest average geosmin concentration was observed in the reservoir with the lowest nutrient and chlorophyll concentrations.
- Taste and odor events were not confined to summer months, and elevated geosmin concentrations were observed in several reservoirs during the winter; we suggest that seasonal data be collected and be incorporated into future model development.
- Dissolved geosmin concentrations were strongly dependent upon local environmental factors, complicating efforts to develop generalized, universal models.
- Analyses of algal biomass-specific geosmin production data suggested that inorganic phosphorus limitation was a key factor regulating the cellular production and release of geosmin into the water column of these five reservoirs.

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