Predicting Taste and Odor Events in Kansas Reservoirs – Phase 1

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by

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Project Summary

The production of taste and odor compounds (i.e. geosmin and 2-methyl isoboreol) by blue green algae, or cyanobacteria, can negatively impact the quality of drinking water. Because costs to remove taste and odor compounds from source water can be high, it is not practical to continuously treat water for this. Instead, predictive tools are needed that allow water treatment operators to determine when taste and odor events are most likely to occur. The purpose of this study was to develop a series of models for predicting geosmin concentrations using data collected from different temporal and spatial scales.

We developed water quality models using data collected from five eastern Kansas reservoirs (Big Hill, Cheney, Clinton, Gardner, and Marion). These reservoirs were selected to represent a range of reservoir conditions and sizes in Kansas. Geosmin and associated water quality data were collected from several sample locations at each reservoir at roughly monthly intervals between June and December of 2006. From this data, water quality models were developed to provide predictive tools that can be used estimate geosmin concentrations in real time. Both single and multiple variable water quality models were developed using all of the reservoir data combined (i.e., universal models) and for each reservoir individually.

In addition to the water quality models mentioned above, we developed landscape models using remotely sensed data and GIS techniques. These models were developed to determine if watershed characteristics could be used to predict taste and odor events. These models assessed relationships between normalized difference vegetation index (NDVI) values, which are correlated with green plant biomass and vegetation cover

within the watershed, and geosmin. Because suitable long-term geosmin and associated water quality data were not available for the five study reservoirs, we used data from two drinking water reservoirs in Oklahoma.

Moderate-resolution Imaging Spectroradiometer (MODIS) 16-day composite Normalized Difference Vegetation Index (NDVI) 250-meter resolution data from the NASA Terra and Aqua remote-sensing satellites was evaluated for its ability to detect and monitor changes in water quality (possible algal blooms) for a series of federal reservoirs in Kansas. MODIS NDVI data values were extracted for each of the water bodies for each of the 23 composite periods in 2006, and enhanced to highlight possible algae blooms in the reservoirs.

Our study findings, conclusions, and recommendations related to both water quality and watershed models are presented below:

1. Elevated geosmin concentrations (>10 ng/L) were observed in all of the reservoirs except Gardner. Taste and odor compounds were common in the summer in most of the reservoirs, and in the winter in two of the reservoirs (Big Hill and Clinton). The lack of taste and odor events in the eutrophic Gardner, combined with the presence of taste and odor events in the mesotrophic Big Hill, suggest that trophic state alone is not a good indicator of taste and odor events in Kansas reservoirs.
2. A universal water quality model using data from four of the reservoirs (Gardner data was excluded) was developed that explained 36% (coefficient of determination $r^2 = 0.36$) of the variation in geosmin concentrations using the single variable orthophosphorus (PO_4). A three-variable universal model was also

developed that explained 53% of the variation in geosmin (GEOS) concentrations using PO_4, temperature, and total phosphorus.

3. The universal reservoir models explained relatively high percentages of the variation in geosmin concentrations considering that data was collected from multiple reservoirs, and multiple sampling sites and dates within each reservoir. However, they likely do not provide enough predictive power to make water treatment decisions. Instead, individual reservoir models explained a greater percentage of the variation in geosmin concentrations in most reservoirs. Therefore, individual reservoirs models, or models developed for reservoirs with similar characteristics such as size, depth, and trophic state, are likely needed to predict taste and odor events.
4. Of the study reservoirs, the individual models for Big Hill explained the greatest percentage of the variation in geosmin. The biomass of the cyanobacteria genus Aphanizomenon explained 87% of the variation in geosmin in a single variable model, while Aphanizomenon biomass and PO_4 explained 93% of the variation in geosmin in a two-variable model.
5. Significant one and three variable models were also developed that explained between 50-82% and 33-72% of the variation in geosmin for Clinton and Marion, respectively. Surprisingly, we were unable to develop any significant models for geosmin using the data collected from Cheney. Models were not developed for Gardner because it did not experience taste and odor events during the study.
6. Watershed models were developed and showed that there was a significant correlation between NDVI values and December geosmin concentrations in

Eucha Reservoir. Although this relationship was based on a limited number of points, it does suggest that watershed characteristics may provide some indication of potential taste and odor events in drinking water reservoirs.

7. Significant models were developed for predicting geosmin concentrations using both water quality variables and watershed data. However, it is important to note that the models have not been tested and their accuracy in predicting actual taste and odor events in a water treatment framework is unknown. Therefore, additional sampling and data is needed to test the models in the five study reservoirs, and in a larger group of reservoirs to determine their applicability across reservoir types.
8. MODIS NDVI 16-day composite data may provide a means of post-facto mapping and monitoring of possible algal blooms within reservoirs. Limitations of the methodology, however, remain. The 16-day compositing period limits real-time monitoring of bloom events, and the NDVI values should be calibrated with on-lake sampling of algal concentrations to establish a detection point (minimum concentration of algae to be detectable by satellite sensors) in order to both avoid false positives and missed detections. Water levels should be taken into account as well; if a reservoir is sufficiently low that vegetation appears on exposed mudflats (e.g., Kanopolis Lake in 2006), the NDVI will be high and should not be misinterpreted as an algae bloom.

Study Rationale

Taste and odor events impact the quality of drinking water obtained from lakes and reservoirs throughout Kansas (e.g. Arruda and Fromm 1989; Smith *et al.*, 2002; Wang *et al.*, 2005; Christensen *et al.* 2006). While a number of microorganisms produce organic compounds (i.e. geosmin and 2-methylisoborneol – MIB) that affect the taste and smell of drinking water, taste and odor events are most often associated with blooms of blue-green algae or cyanobacteria (e.g. Izaguirre *et al.*, 1982; van der Ploeg *et al.*, 1992; Saadoun *et al.*, 2001). Because humans can detect geosmin and other taste and odor compounds at very low concentrations (5-10 ng/L, Taylor *et al.*, 2006), there is only a short window of opportunity to treat a developing taste and odor event before customer complaints are received. Furthermore, costs associated with such treatment can be high, and it is not practical or feasible for most facilities to continuously treat water for taste and odor. Instead, predictive tools are needed to determine when taste and odor events are most likely to occur (Izydorczyk *et al.*, 2005).

The purpose of this study was to develop a series of predictive models that could be used as early indicators of developing taste and odor events in Kansas reservoirs. Specifically, we explored two types of models that operate at different spatial and temporal scales. First, we developed models for predicting geosmin concentrations using collected water quality variables (Section 1). Second, we developed watershed models using watershed characteristics within a watershed to predict geosmin concentrations (Section 2). Third, we used Moserate-resolution Imaging Spectroradiometer (MODIS) data to document changes in water quality from ten Kansas reservoirs. The results from these modeling efforts are presented below in three sections.

1. Water Quality Models

Introduction

One approach to managing taste and odor events is to simply measure the concentrations of geosmin or other taste and odor compounds on a regular basis. Measured concentrations of geosmin could then be used treat before concentrations are high enough for human detection in source water. However, analysis of geosmin concentrations requires a great deal of technical training and equipment, and sending samples to a contract lab can be very expensive and results are often not received in a time frame that allows for water treatment decisions based on current reservoir conditions. Alternatively, there may be correlations between geosmin concentrations and water quality variables that are easier and more cost effective to measure. For example, it is possible that changes in cyanobacterial biomass could be monitored using laboratory counts or with *in-situ* fluorometers to predict the onset of taste and odor events (e.g., Izydorczyk *et al.*, 2005). Similarly, a number of water quality variables can affect cyanobacterial biomass, and changes in these variables may be used to monitor and potentially predict the occurrence of taste and odor events. Potential predictor variables that can affect cyanobacterial biomass and are relatively easy to measure include nutrient concentrations and ratios (Downing *et al.*, 1999; Smith and Bennett, 1999), water clarity (Havens *et al.*, 1998), water temperature and pH (Shapiro, 1990), and food web structure (Hunt *et al.*, 2003).

A theoretical framework for using relationships between geosmin and water quality variables to predict the occurrence of taste and odor events is shown in Figure 1 (V.H. Smith unpublished data, Smith *et al.*, 2002). Geosmin concentrations may be correlated with one or more predictor variables, which are easier and more cost effective

to measure. The predictor variable(s) could then be used to estimate geosmin concentrations and ultimately influence when to treat or not treat drinking water.

The goal of this section of the study was to develop a series of relatively simple models for predicting geosmin concentrations using measured water quality variables from five Kansas reservoirs. Furthermore, we were interested in determining if "universal" models developed using all of the data from the five reservoirs combined would provide as much predictive power as models developed for each reservoir individually.

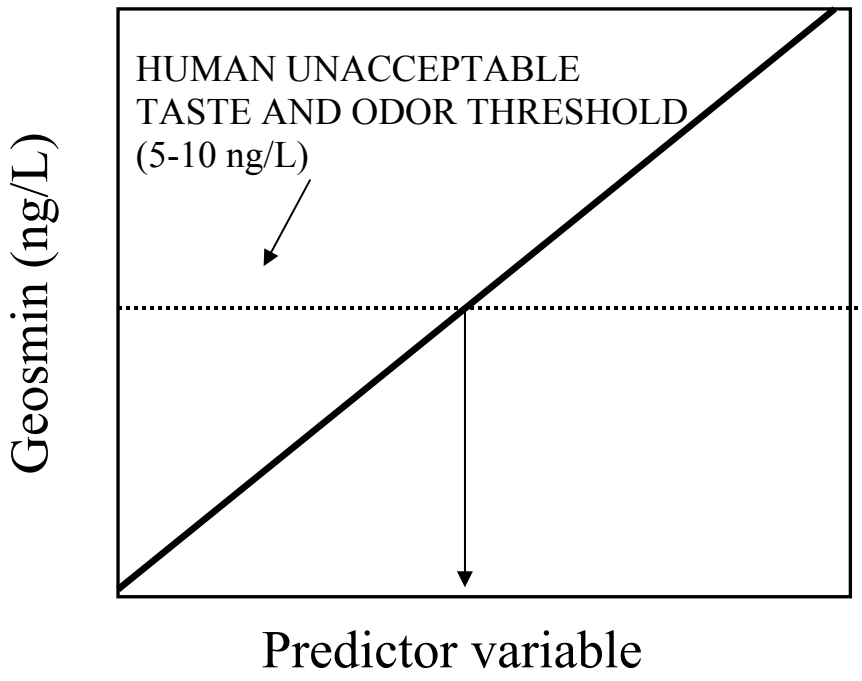


Figure 1. Theoretical framework for using water quality models to predict taste and odor events in drinking water reservoirs. Concentrations of geosmin may be correlated with a series of predictor variables that are easier and more cost effective to measure. The predictor variable could then be used to estimate geosmin concentrations and influence treatment decisions. Figure modified from V.H. Smith (unpublished data).

Methods

Reservoir Sampling and Data Collection

Five Kansas reservoirs were selected to study taste and odor events: Big Hill, Cheney, Clinton, Gardner, and Marion (Figure 2). These reservoirs were selected with the help of Ed Carney, Kansas Department of Health and Environment (KDHE) and personnel from the Kansas Water Office (KWO), to represent a range of reservoir conditions and sizes in Kansas. Furthermore, each of these reservoirs has experienced taste and odor events in the past (E. Carney, KDHE, personnel communication). The five reservoirs were sampled at roughly monthly intervals from June to October 2006, while Big Hill and Clinton were also sampled several times in December and/or January 2007 during specific taste and odor events. Table 1 shows the sampling schedule .

A number of chemical, physical, and biological variables were measured at each reservoir (Table 2). Samples were collected from three sampling sites to assess spatial variability in each reservoir: one in the riverine zone, one in the transition zone, and one in the lacustrine zone. If a reservoir had inflow from more than one tributary, we sampled from the tributary that was associated with the stream (river) having the greatest discharge. At each site, *in-situ* measurements of dissolved oxygen, turbidity, specific conductance, pH, and water temperature were obtained with a Horiba field water quality checker at 1m depth intervals. A Secchi Disk was used to measure water transparency.

Two water samples were collected at each site from a depth of 1.5m below the surface and returned to the Kansas Biological Survey Ecotoxicology Laboratory for analysis of nutrients (total and dissolved nitrogen, phosphorus), chlorophyll *a*, and geosmin concentrations.

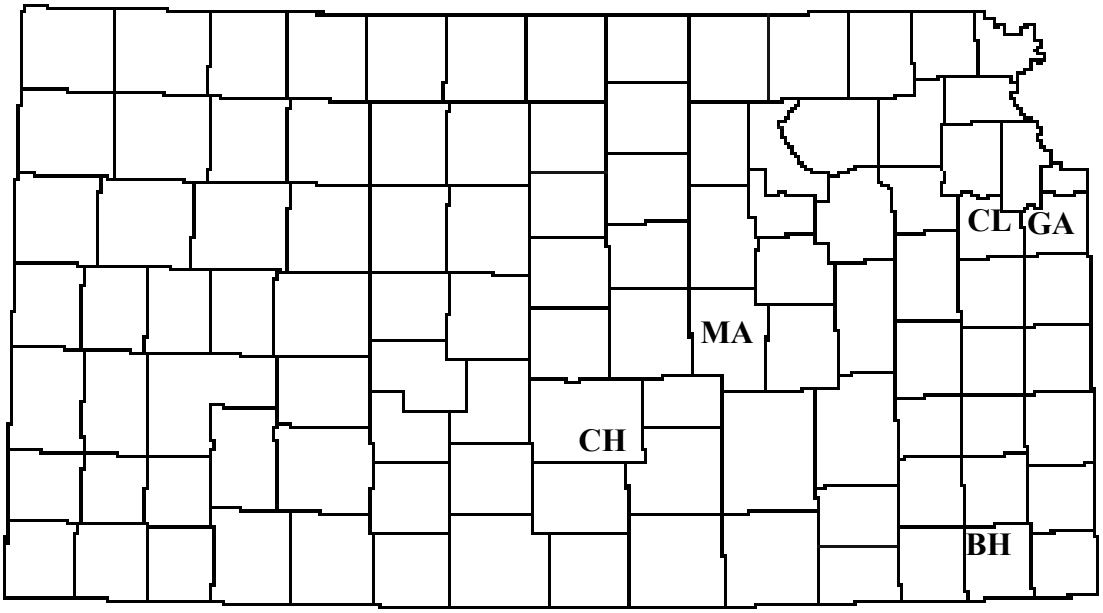


Figure 2. Reservoir locations: BH – Big Hill; CH – Cheney; CL – Clinton; GA – Gardner; and MA – Marion.

Table 1. Sampling schedule for each of the five reservoirs over the course of the study.

	Big Hill	Cheney	Clinton	Gardner	Marion
Sample Date	6-27-06	6-26-06	7-3-06	6-27-06	6-26-06
	7-12-06	7-10-06	7-25-06	7-12-06	7-10-06
	7-24-06	7-25-06	8-17-06	8-8-06	7-25-06
	8-8-06	8-7-06	8-30-06	9-25-06	8-7-06
	9-25-06	9-6-06	9-13-06	10-18-06	9-6-06
	1-2-07	10-2-06	10-5-06		10-2-06
			12-15-06		

Table 2. Water quality and biological variables used in model development.

NO_2-N	*Aphanizomenon* Biovolume
NO_3-N	% *Aphanizomenon*
NH_3-N	*Microcystis* Biovolume
Total Nitrogen	% *Microcystis*
PO_4-P	*Anabaena* Biovolume
Total Phosphorus	% *Anabaena*
TN:TP ratio	*Oscillatoria* Biovolume
Chlorophyll *a*	% *Oscillatoria*
Phaeophytin *a*	Total Biovolume of other taxa
Water temperature	% Other Taxa
Turbidity	Total Cyanobacterial Biovolume
Dissolved oxygen	% Total Cyanobacteria
Specific conductance	Total Algal Biomass
pH	
Secchi Disk	

Nutrient concentrations were determined colorimetrically (APHA, 1995) with a Lachat analyzer (Model 4200). Samples for dissolved nutrients (NO_3-N, NH_4-N, and PO_4-P) were filtered through Gelman Science's ion chromatography acrodisc filters (0.45 μm) before analysis. Total nitrogen (TN) and total phosphorus (TP) concentrations were determined using the automated colorimetric procedures after persulfate digestion of unfiltered samples (Ebina, *et al.*, 1983). All nutrient analysis was performed within 48 hours of sample collection.

Chlorophyll *a* concentrations were determined by first filtering the algae from the water samples onto Whatman GF/F glass fiber filters. The filters were folded in fourths and frozen to rupture the cells. Chlorophyll *a* concentrations were extracted in 90% basic methanol (10% saturated $MgCO_3$) for at least 24 hours. The concentration of chlorophyll *a*, corrected for phaeophytin *a*, was then determined by measuring the fluorescence of the

sample with the Optical Technologies fluorometer before and after acidification (APHA, 1995).

Geosmin concentrations were also determined at the Ecotoxicology Laboratory using the solid phase extraction (SPE) technique followed by gas chromatography and mass spectrometry (GC/MS) as refined by Pan (2002). The methodological detection limit for geosmin was 5 ng/L.

Water samples from each site were preserved in Lugol's solution for taxonomic determinations of cyanobacteria. We identified and enumerated cyanobacteria following procedures outlined in Utermöhl (1958) and APHA *et al.* (1998). Briefly, 5 ml's from each sample were settled in a chamber for 24 hours. A total of 25-50 microscope fields were then randomly chosen and counted at greater than 400x magnification. Cyanobacteria were identified to genus, and biovolume estimates were provided for the most common taxa including *Aphanizomenon*, *Anabaena*, *Microcystis*, and *Oscillatoria*. We focused specifically on these taxa because they tend to dominate cyanobacterial communities in Kansas reservoirs (F. deNoyelles, personal communication). We also quantified the biovolume of all additional organisms using the same methodology so that we could determine the percentage of cyanobacterial biovolume in each sample.

In-situ Hydrolab multiprobe units were placed at a depth of 1.5m below the surface in three of the reservoirs (Clinton Lake, Gardner Lake, and Marion Reservoir). The multiprobe units were outfitted with a cyanobacteria sensor that uses fluorescence technology to provide real-time measurements of phycocyanin (cyanobacterial pigments) concentrations. The probes were programmed to collect data at 15-30 minute intervals.

Additional Data Requests

In an effort to increase our dataset for model development (see below), we requested previously collected water quality and taste and odor data from all public water systems in the state of Kansas that used reservoirs or lakes as sources of raw water in 2004. In addition, we sent out a broader request for data to more than 400 regional limnologists. Despite these data solicitation efforts we received very little data, and those data that we did receive that included information on geosmin concentrations did not have predictor variables (i.e. water quality data) associated with the datasets. The exceptions to this included data provided by United States Geological Survey (USGS, Lawrence, KS) and Val Smith at the University of Kansas (KU). However, there were concerns that data from these other sources was collected using different methodologies and were not necessarily compatible with the reservoir sampling conducted in this study. Therefore, models were developed using only data collected by the KBS as part of the current study (see below).

In addition to the five reservoirs mentioned above, we had originally proposed to sample a number of reservoirs as they experienced taste and odor events. To accomplish this, we asked that water treatment personnel in the state of Kansas notify KBS within 24-hours of identifying or suspecting the onset of a taste and odor event in their reservoir. We only received one notification of a taste and odor event from Hillsdale Reservoir; however, when we sampled the reservoir we found no signs of an event.

Model Development

Regression analysis was used to develop relatively simple models for estimating geosmin concentrations from the collected water quality variables (Table 2). Similar

modeling approaches have recently been used to estimate geosmin and additional water quality parameters by the USGS in Kansas streams and reservoirs (e.g. Mau *et al.*, 2004; Christensen *et al.*, 2006). Prior to model development, all of the water quality variables were checked for normality. When data did not meet the assumption of normality, $\log_{10}$ transformations were conducted. Two types of regression analyses were used to develop predictive geosmin models. First, we used best-subsets regression, which provides the two one-variable models with the highest coefficient of variation (r^2) values, the two two-variable models with the highest r^2 values, and so on (Sokal and Rohl, 1995). Second we used step-wise multiple regression, which is a procedure that adds variables to a model one at a time if they increase the significance of the model. It adds variables until no more can be added to increase the r^2 of the model.

Each of the regression procedures provided a number of statistically significant regression models (alpha ≤ 0.05). Therefore, there were several considerations that we took into account when selecting the "best" regression models. First, from a statistical standpoint we evaluated the r^2 value (coefficient of determination) of each model, which provides a measure of how much of the variation in geosmin concentrations is determined or explained by the predictor variable(s). Models with high r^2 values were selected for further consideration. Second, from a water treatment perspective, we retained models that included variables that were relatively easy and inexpensive to collect. For example, if two models had relatively similar r^2 values, but the model with the highest r^2 (better predictor of geosmin) included variables that were relatively difficult to collect, we presented the model with the slightly lower r^2. This was not

always possible and some of the more promising models with analytically "costly" variables are included in this report.

Both single and multiple variable models were developed for the individual reservoirs and for "universal" reservoir models in which all of the data were combined from four of the five reservoirs. Data from Gardner Lake was not included in the model development because taste and odor events were rare during the study period (see results below).

We also incorporated data collected as part of the United States Army Corps of Engineers (USACE) Kansas City District's monitoring program into our model development. In the summer of 2007, a total of 39 geosmin samples were collected from 18 reservoirs located over a broad geographic region including nine in Kansas (Clinton Lake, Hillsdale Lake, Kanopolis Lake, Melvern Lake, Milford Lake, Perry Lake, Pomona Lake, Tuttle Creek Lake and Wilson Lake), seven in Missouri (Blue Springs Lake, Harry S. Truman Lake, Long Branch Lake, Longview Lake, Pomme de Terre Lake, Smithville Lake and Stockton), one in Nebraska (Harlan County Lake) and one in Iowa (Rathbun Lake).

The data from the USACE was used in two ways in model development. First, we added it to our larger "universal" data set (Big Hill, Clinton, Cheney and Marion) to reevaluate the relationships between geosmin and water quality conditions with this additional data from multiple reservoirs. Stepwise and best subset regressions were used on the combined data set (KBS and USACE) as described above to determine if it provided more predictive power than the original dataset (KBS alone). Second, we used stepwise and best subset regressions to develop predictive models for the USACE data

alone. It is important to point out that the USACE dataset included nutrient data only. Therefore, only seven variables were used to create these additional models (NO_2, NO_3, NH_3, PO_4, TN, TP and TN:TP).

Results

General Water Quality Conditions

Water quality conditions varied considerably in the five reservoirs (Table 3). In general, total nutrient and chlorophyll concentrations and turbidity were the lowest in Big Hill and the highest in Marion. There were also strong positive relationships between TP and chlorophyll ($\log_{10}Chl = 0.14 + 0.67(\log_{10}TP)$, $r^2=0.65$) and TN and chlorophyll ($\log_{10}Chl = -2.21 + 1.23(\log_{10}TN)$, $r^2=0.61$) in the reservoirs (Figure 3). We used the ranges of total nutrient and chlorophyll concentrations presented in Smith *et al.* (1999) to characterize the trophic state of each reservoir. Big Hill was classified as mesotrophic, while Cheney, Clinton, and Gardner were classified as eutrophic, and Marion was classified as hypereutrophic.

Table 3. Average water quality variables collected at each reservoir. Data represents average values from multiple samples collected at each reservoir over the course of the study from multiple sites. Standard deviations are in parentheses.

Lake	Geosmin (ng/L)	pH	Cond. (mS cm^{-1})	DO (mg/L)	Turb. (NTU)	Secchi Disk (cm)	Water Temp. (˚C)	NO_3^--N (mg/L)	NH_3-N (mg/L)	TN (mg/L)	PO_4^{-3}-P (µg/L)	TP (µg/L)	TN/TP	Chl a (µg/L)
Big Hill	**11**	**8.29**	**0.23**	**8.54**	**12**	**142**	**23.1**	**0.07**	**35.1**	**581**	**6.8**	**23.4**	**29**	**12.7**
	(9.3)	(0.4)	(0.02)	(1.51)	(3.4)	(28)	(8.0)	(0.10)	(34.1)	(92)	(5.7)	(7.4)	(17.3)	(5.0)
Cheney	**7**	**8.63**	**0.79**	**9.10**	**62**	**49**	**25.7**	**0.04**	**27.1**	**884**	**15.5**	**85.2**	**11**	**27.2**
	(3.0)	(0.18)	(0.01)	(1.58)	(43.8)	(16)	(3.05)	(0.03)	(24.5)	(153)	(6.8)	(35.7)	(1.93)	(7.9)
Clinton	**11**	**8.43**	**0.30**	**9.60**	**34**	**69**	**22.7**	**0.07**	**21.2**	**655**	**13.7**	**61.0**	**12**	**21.3**
	(8.1)	(0.31)	(0.03)	(1.96)	(22.3)	(30)	(7.93)	(0.05)	(15.5)	(108)	(6.9)	(24.1)	(3.6)	(6.4)
Gardner	**3**	**8.29**	**0.36**	**7.94**	**25**	**78**	**23.8**	**0.12**	**67.6**	**800**	**23.1**	**78.7**	**12**	**25.6**
	(1.1)	(0.50)	(0.46)	(3.20)	(12.1)	(23)	(5.5)	(0.24)	(85.1)	(336)	(29.9)	(56.6)	(3.2)	(23.7)
Marion	**8**	**8.60**	**0.53**	**8.00**	**94**	**42**	**24.3**	**0.05**	**44.5**	**1734**	**70.2**	**206.3**	**7**	**50.6**
	(8.5)	(0.21)	(0.05)	(1.19)	(73.3)	(16)	(2.84)	(0.07)	(61.9)	(1970)	(33.3)	(73.3)	(1.8)	(35.9)

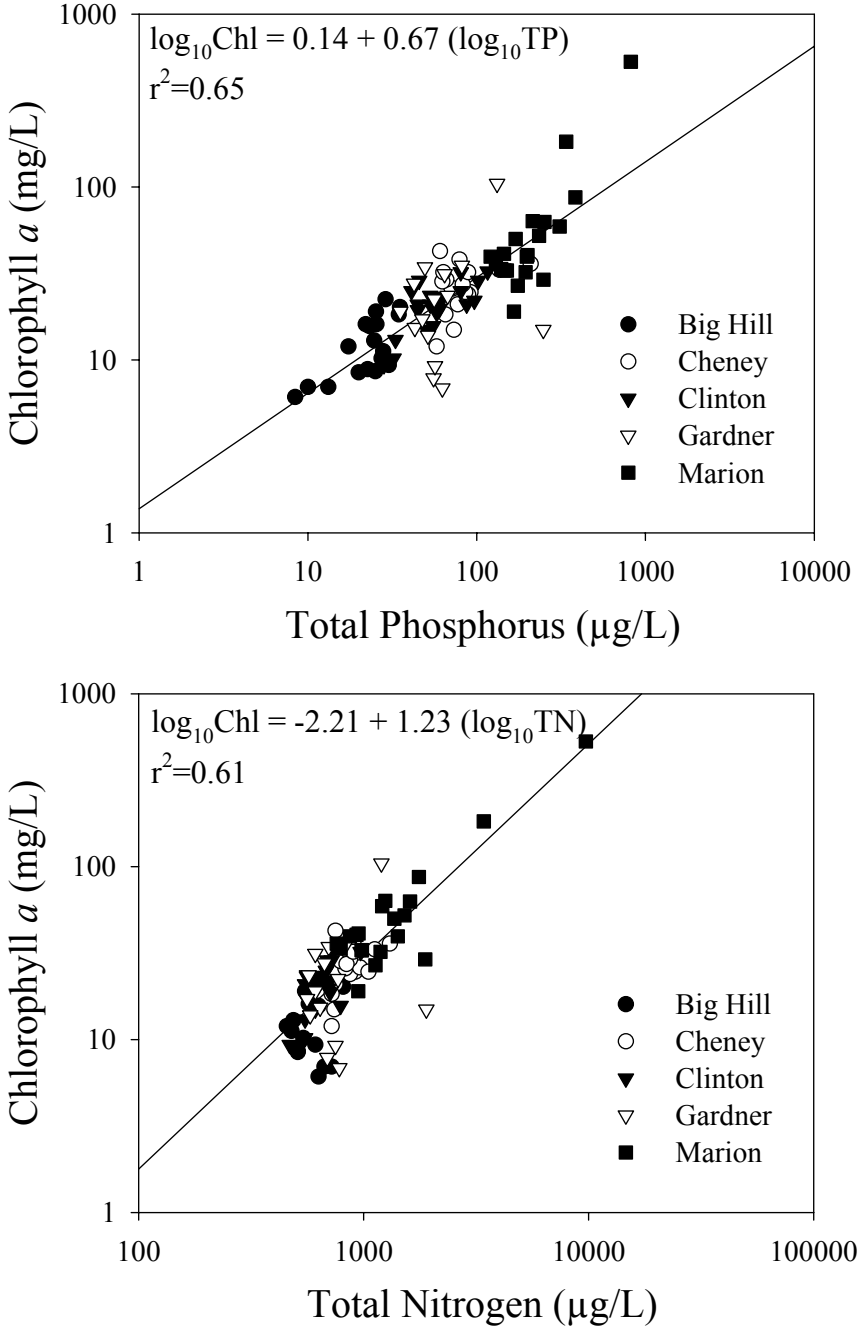


Figure 3. Significant regression relationships between chlorophyll *a* and total nutrient concentrations in the dataset from the five Kansas reservoirs.

The reservoirs also differed in their mixing/stratification patterns. Figure 4 shows examples of typical summer temperature profiles from the five reservoirs that were collected during the study on various sample dates. Big Hill and Gardner showed strong patterns of thermal stratification, while the remaining three reservoirs did not thermally stratify. Strong thermal stratification was not observed on any sample date in Clinton, Cheney, or Marion.

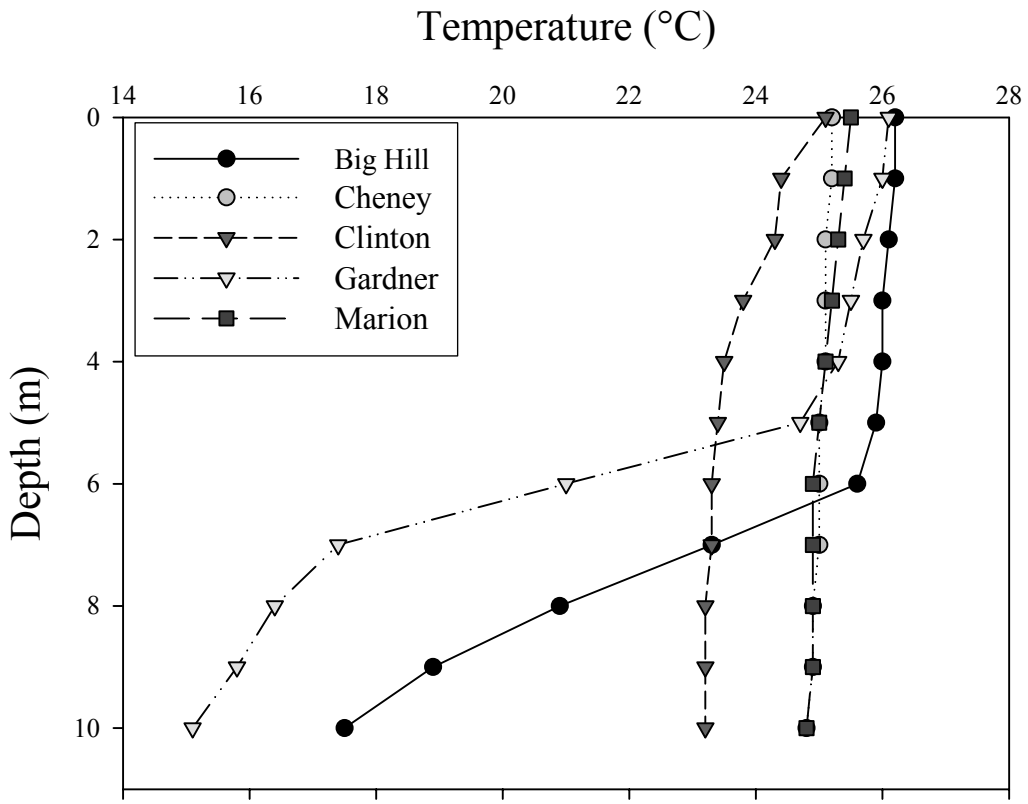


Figure 4. Temperature profiles from each of the five Kansas reservoirs. The profiles were collected on various dates between June 1 and September 1, 2006 to show differences in stratification patterns.

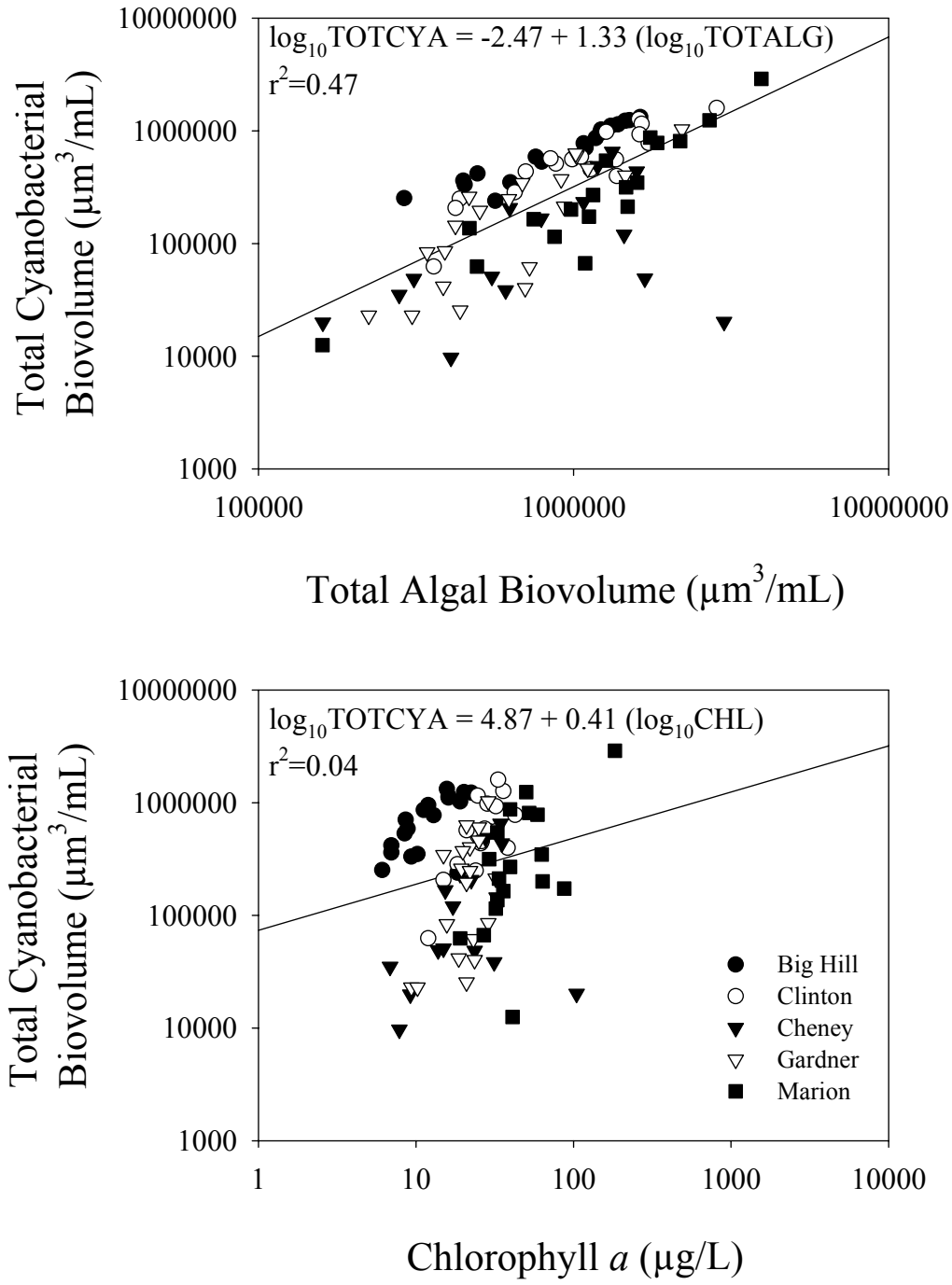


Figure 5. Regression relationships between total cyanobacterial biovolume (TOTCYA) and total algal biovolume (TOTALG) and TOTCYA and chlorophyll concentrations (CHL).

There was a positive relationship between total algal biovolume and total cyanobacterial biovolume ($\log_{10}$TOTCYA = -2.47 + 1.33($\log_1$TOTALG), r^2=0.47), but not between chlorophyll *a* concentrations and total cyanobacterial biovolume ($\log_{10}$TOTCYA = 4.87 + 0.41($\log_{10}$CHL), r^2=0.04) in the reservoirs (Figure 5). Big Hill consistently had the highest percentage of cyanobacteria biovolume (between 65-90%, Figure 6) followed by Cheney (between 35-70%,Figure 7). *Aphanizomenon* and *Anabaena* were the dominant cyanobacterial taxa in Big Hill and Cheney respectively. Cyanobacteria tended to account for less than 50% of the total algal biovolume in Clinton (between 10-45%,Figure 8), Gardner (between 3-50%,Figure 9), and Marion (between 15-45%, Figure 10). *Anabaena* was the dominant taxa of cyanobacteria in these three reservoirs (Figures 8-10).

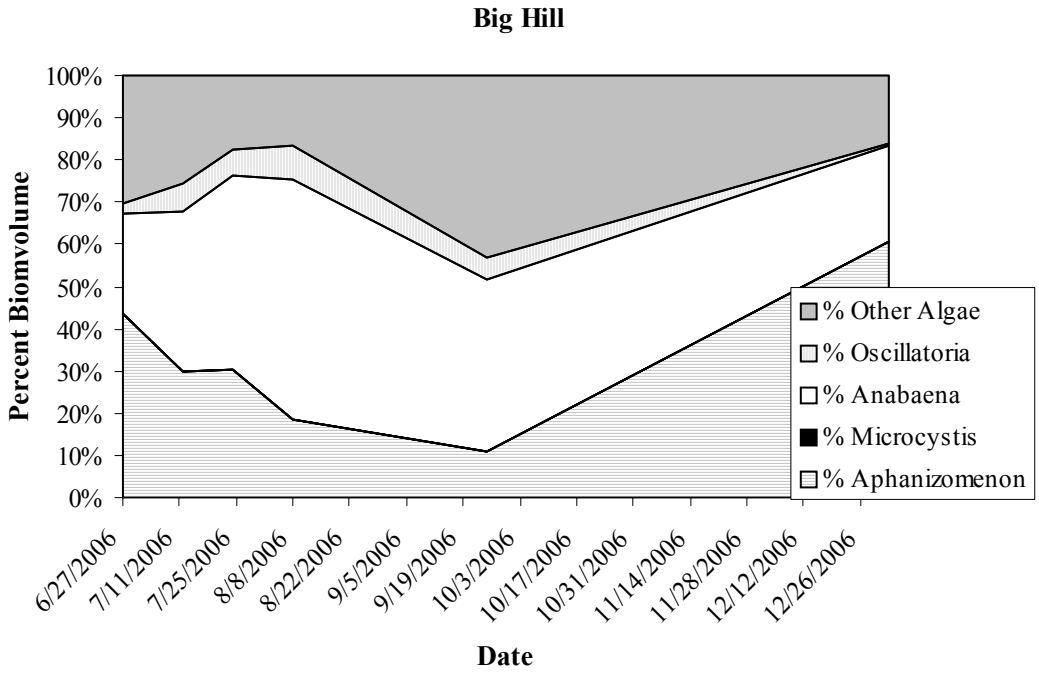


Figure 6. Percent biovolume data for cyanobacterial taxa in Big Hill.

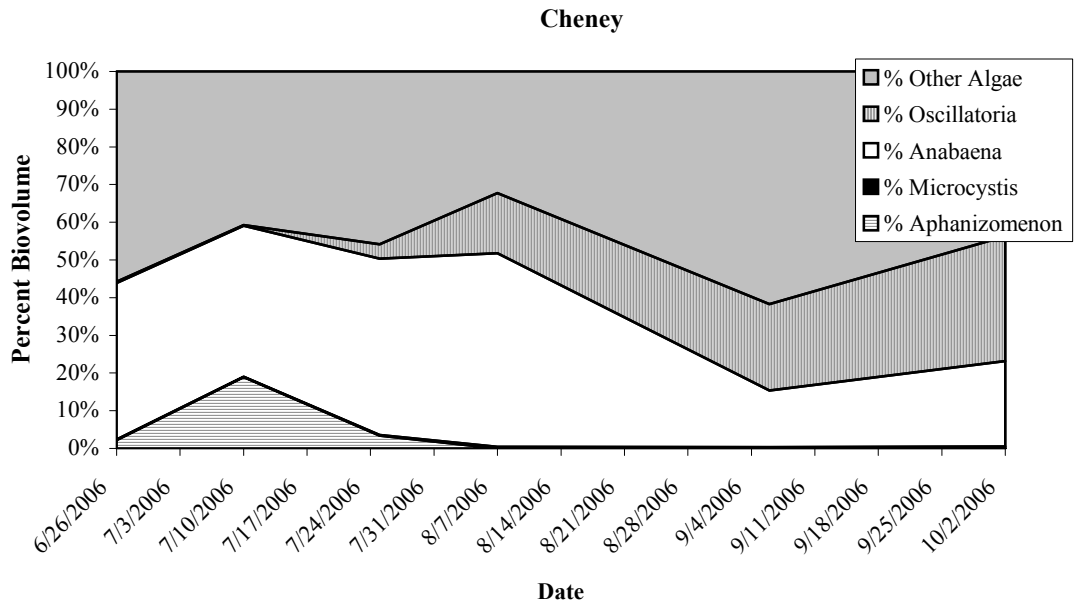


Figure 7. Percent cyanobacteria biovolume data for Cheney.

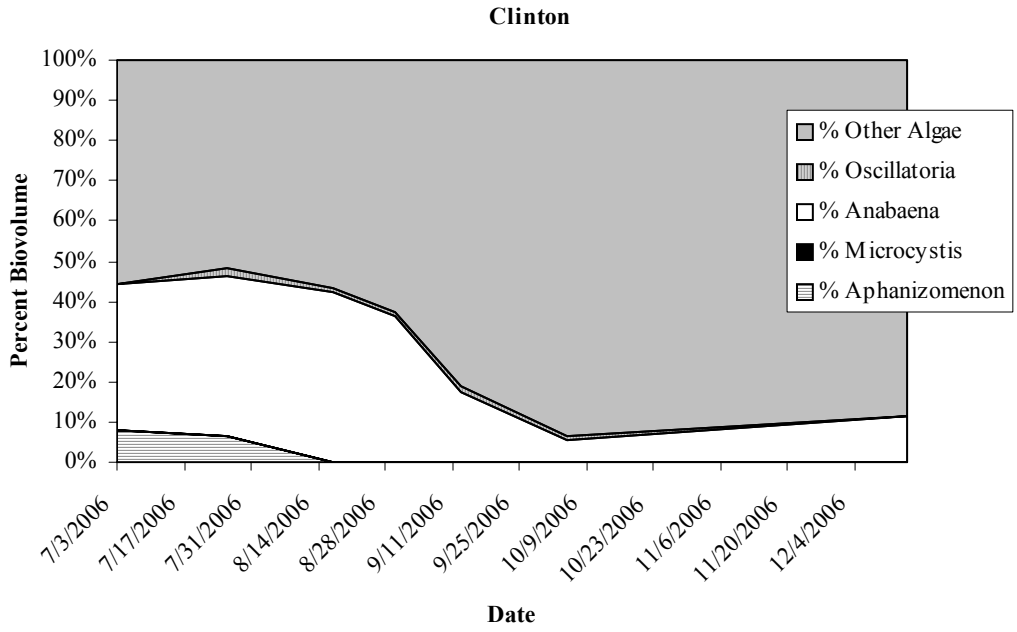


Figure 8. Percent cyanobacteria biovolume data for Clinton.

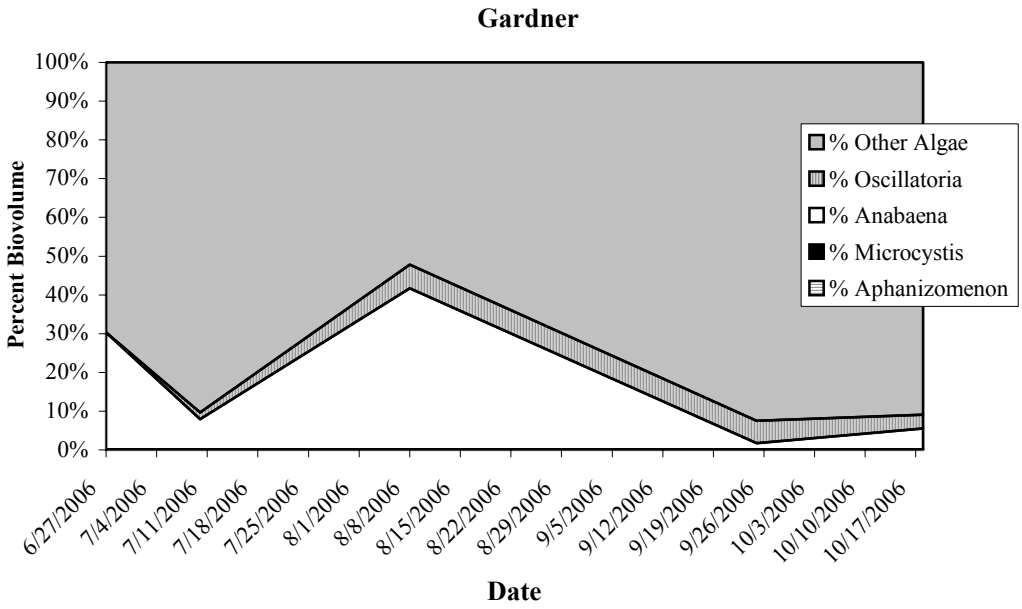


Figure 9. Percent cyanobacteria biovolume data for Gardner.

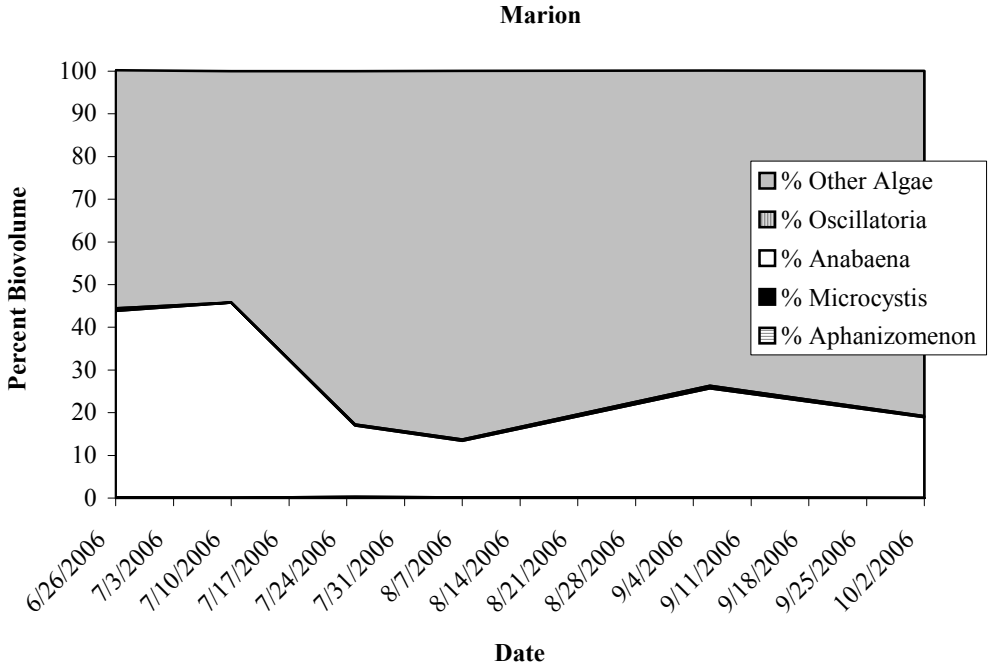


Figure 10. Percent cyanobacteria biovolume data for Marion.

Taste and Odor Compound

Geosmin concentrations were below human detection limits (5 ng/L) in the majority of samples collected from Gardner Lake. In contrast, geosmin concentrations exceeded human detection limits in 67%, 89%, 86%, and 55% of the samples collected from Big Hill, Cheney, Clinton, and Marion respectively (Figure 11). Differences also existed in the temporal patterns of geosmin concentrations in the reservoirs. In two of the reservoirs, Big Hill and Clinton, the highest geosmin concentrations were observed in December (Figure 12). In Marion, the highest geosmin concentrations were observed in July and September when dense algal blooms were visually observed in the reservoir. There was much less temporal variation in geosmin concentrations in Cheney and Gardner (Figure 12). Additionally, there was little variation in geosmin concentrations in the three zones of each reservoir (Figure 12).

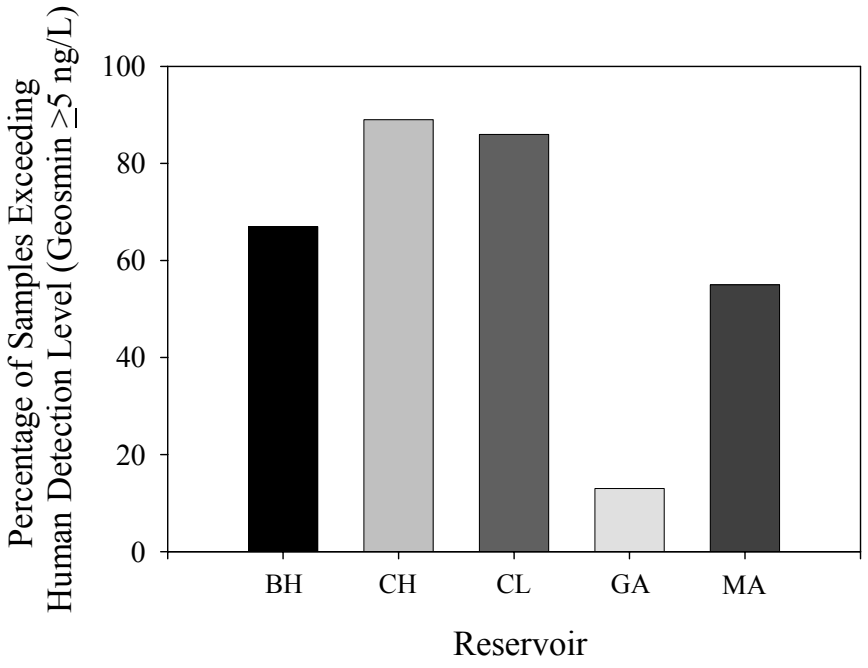


Figure 11. Percentage of reservoir samples that had geosmin concentrations that exceeded human detection limits (5 ng/L) throughout the course of the study.

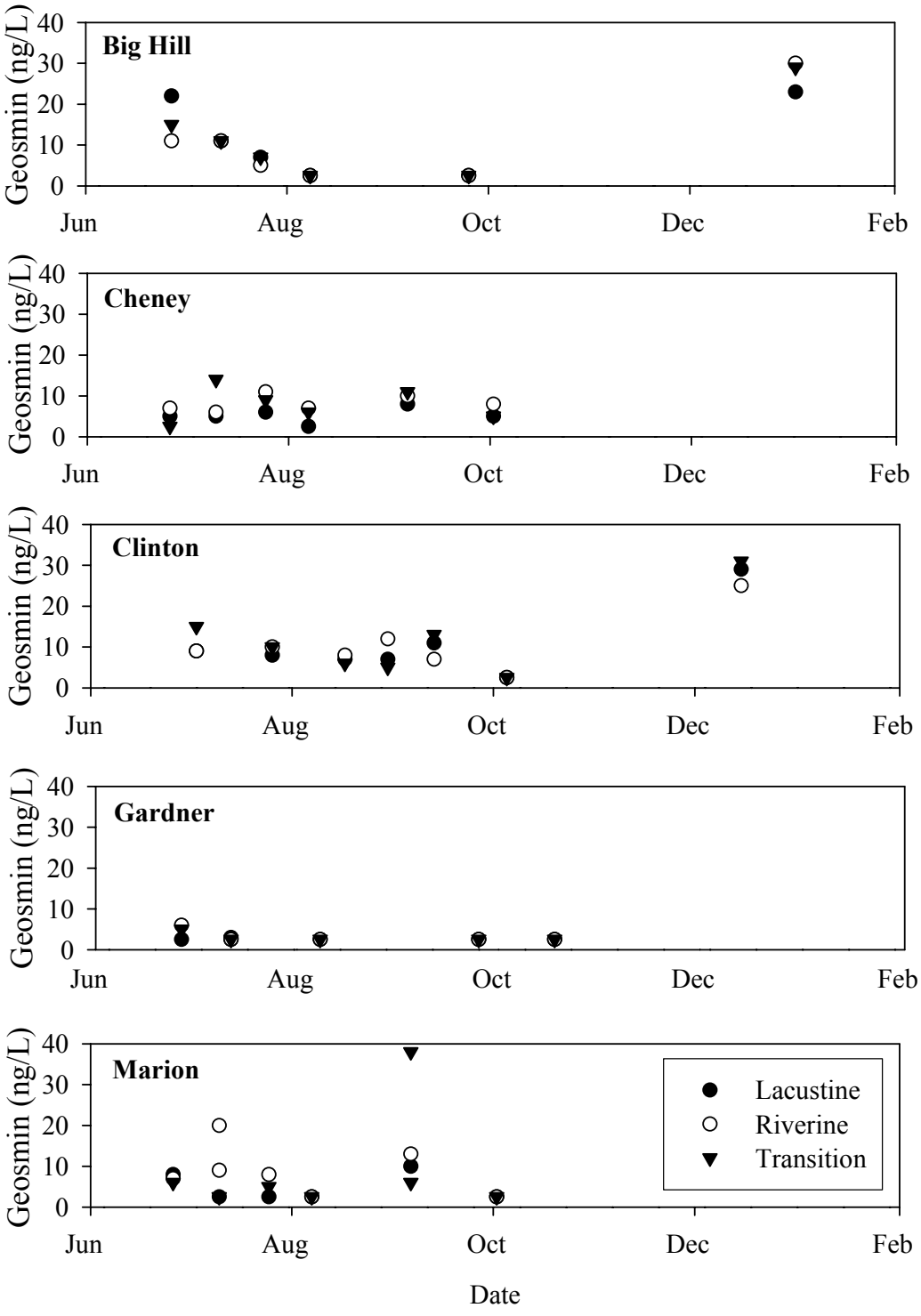


Figure 12. Geosmin concentrations measured over the course of the study at each reservoir site.

Relative Fluorescence Concentrations

Fluorometers, which were programmed to record relative phycocyanin concentrations at 1-hour intervals, were placed 1.5m below the surface in three of the reservoirs: Clinton, Gardner, and Marion. However, shortly after the probe was placed in Gardner it was determined to be non-functional. Therefore, data is only presented for Clinton and Marion (Figure 13). The fluorescence values are relative values that can be compared within individual reservoirs, but not necessarily between reservoirs.

Phycocyanin concentrations peaked in early October in Clinton and relatively high concentrations were also observed towards the end of October (Figure 13). A similar pattern was observed in Marion where phycocyanin concentrations were highest when the probe was placed in early October, and then began to decrease by the middle of October (Figure 13).

Model Development

Exploratory models were originally developed using several scenarios. Models were first developed individually for each of the three zones of the reservoirs (lacustrine, transition, and riverine) as well as models using all of the data from each of the three sampling sites in each reservoir combined. However, there were very few differences in geosmin concentrations between the three sites in most reservoirs (Figure 12). Furthermore, models including all of the reservoirs sampling site data combined provided relatively similar predictive power as did the models that used data from each specific site individually (not shown). Because no distinctions were made between the three zones of the reservoirs all of the spatial data were combined for model development.

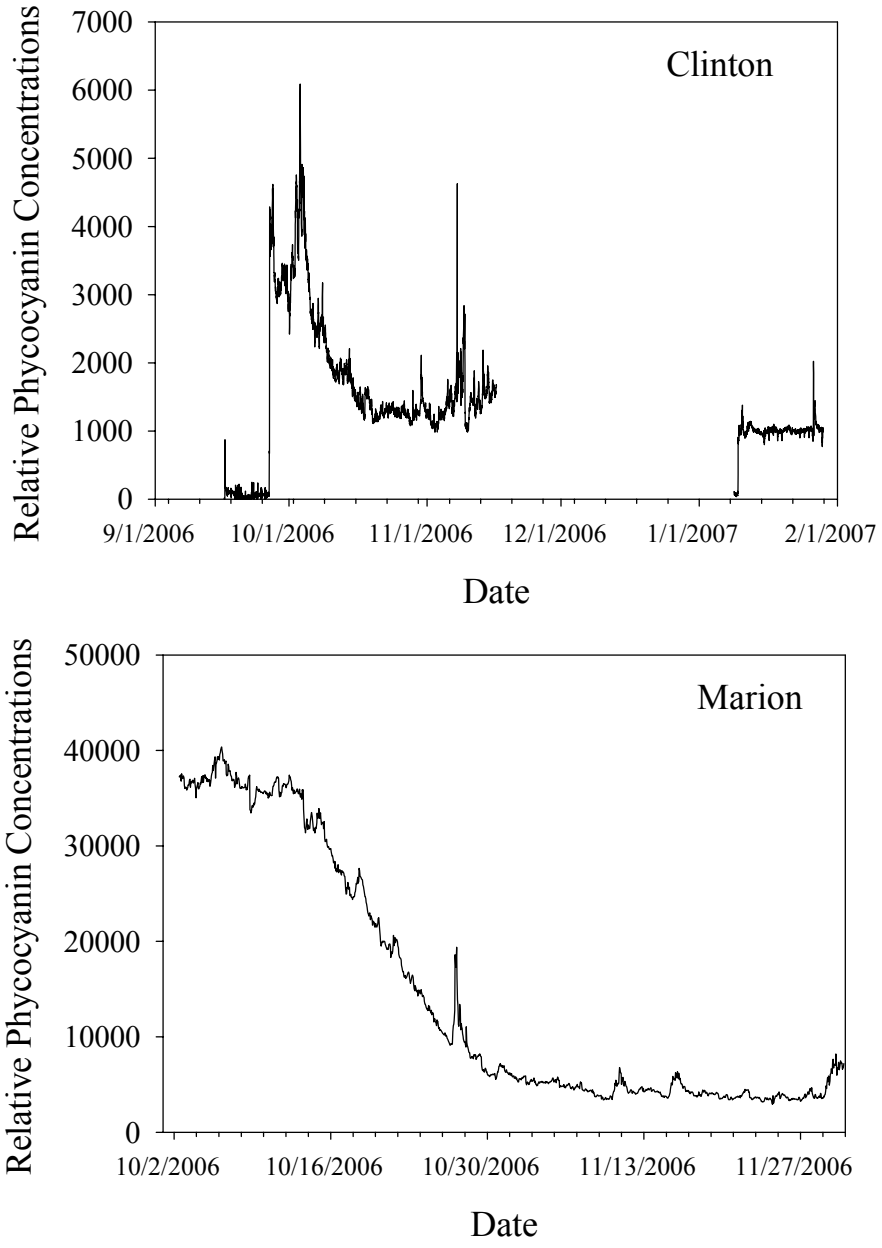


Figure 13. Relative phycocyanin concentrations measured at 1-hour intervals with submersed fluorometers in Clinton and Marion.

All of the models presented below are statistically significant (alpha ≤ 0.05). Regression models are first presented for all of the data combined from each of the four reservoirs (Universal Models) and then for each reservoir individually (Individual Reservoir Models).

Universal Models

Universal regression models were first developed using all of the data from each of the four reservoirs (Big Hill, Clinton, Cheney, and Marion) combined. A single-variable model was developed that explained 36% (r^2 – coefficient of determination) of the variation in geosmin (GEOS) concentrations (Figure 14):

(1) $\log(GEOS) = 1.25 - 0.38 \log(PO_4)$, $r^2=0.36$

where GEOS is geosmin and PO_4 is orthophosphorus. No other significant one-variable models were developed.

A three-variable universal model was developed that explained 53% of the variation in geosmin (GEOS) concentrations:

(2) $\log(GEOS) = 1.45 - 0.61 \log(PO_4) - 0.62 \log(TEMP) + 0.50 \log(TP)$, $r^2=0.53$

where PO_4 is orthophosphorus, TEMP is temperature, and TP is total phosphorus.

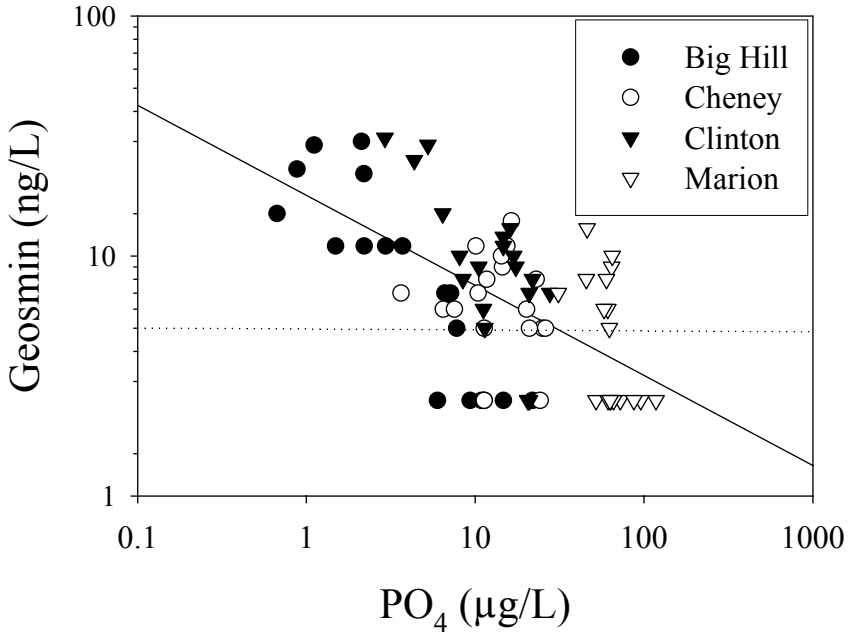


Figure 14. Significant regression relationship between PO_4 and geosmin in all reservoirs. See text for regression equation and r^2 value (Equation 1). Horizontal line corresponds with geosmin concentration of 5 ng/L.

Individual Reservoirs Models

Big Hill Lake

A single-variable quadratic regression model was developed for Big Hill that explained 87% of the variation in geosmin (GEOS) concentrations (Figure 15):

(3) (3) $\log(GEOS) = -0.06 + 0.04(\%APH) - 0.002(\%APH)^2$, $r^2=0.87$

where %APH is the percentage of *Aphanazomenon* biovolume. A second single-variable model was developed for Big Hill that explained 77% of the variation in geosmin (GEOS) concentrations (Figure 15):

(4) $\log(GEOS) = 1.36 - 0.79 \log(PO_4)$, $r^2=0.77$

where PO_4 is orthophosphate.

A two-variable model that explained 93% of the variation in geosmin concentrations was also developed for Big Hill:

(5) $\log(GEOS) = 0.752 - 0.448 \log(PO_4) + 0.012(\%APH)$, $r^2=0.93$

where PO_4 is orthophosphate and %APH is the percentage of *Aphanazomenon* biovolume.

Clinton Lake

A single-variable regression model was developed for Clinton that explained 50% of the variation in geosmin (GEOS) concentrations (Figure 16):

(6) $\log(GEOS) = 0.443 + 0.007(SECC)$, $r^2=0.50$

where SECC is Secchi Disk depth. A second single-variable model was developed for Clinton that explained 43% of the variation in geosmin (GEOS) concentrations (Figure 16):

(7) $\log(GEOS) = 1.34 - 0.029(PO_4)$, $r^2=0.43$

where PO_4 is orthophosphate.

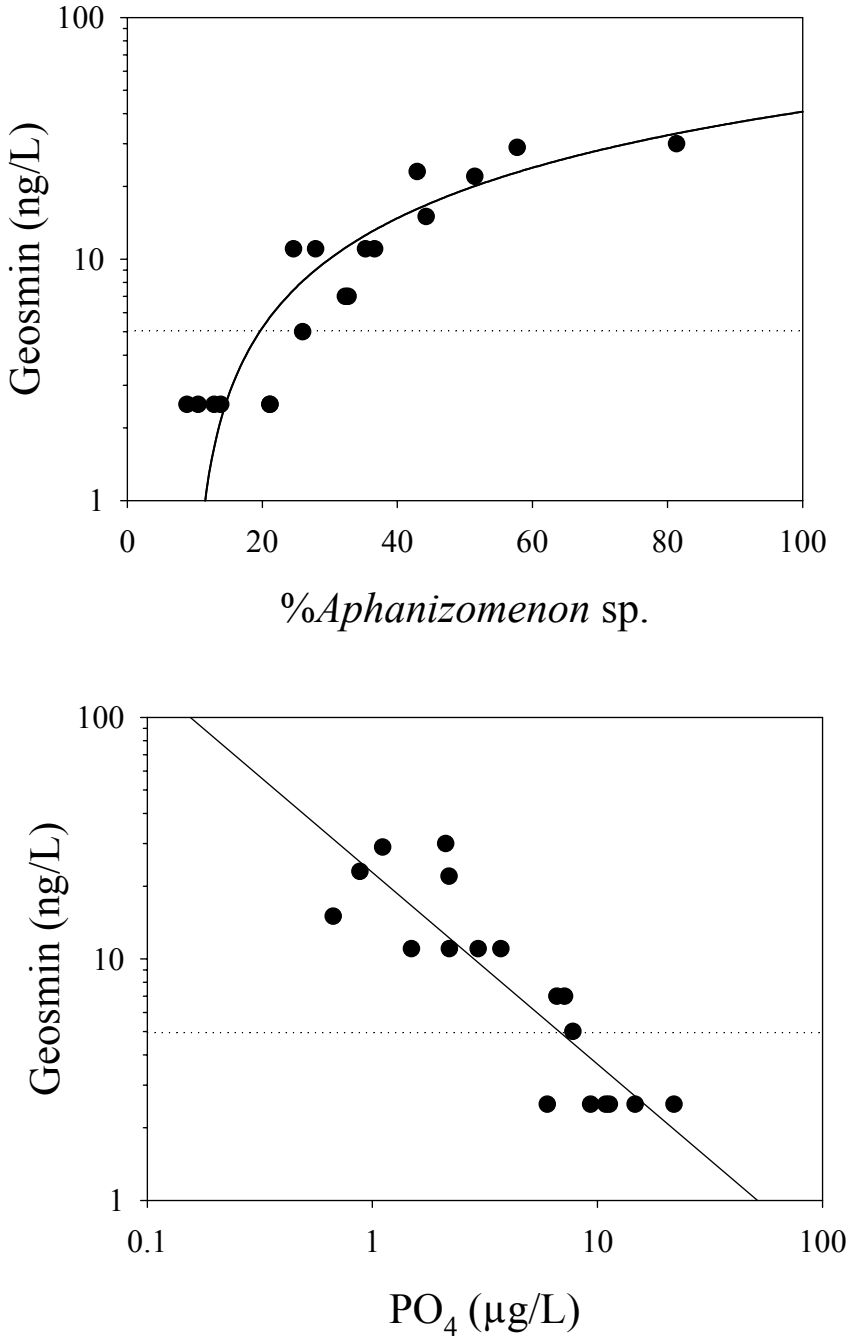


Figure 15. Significant regression relationship between % Aphanizomenon biovolume and geosmin and PO_4 and geosmin in Big Hill. Horizontal line corresponds with geosmin concentrations of 5 ng/L. See text for regression equations and r^2 values (Equations 3 and 4).

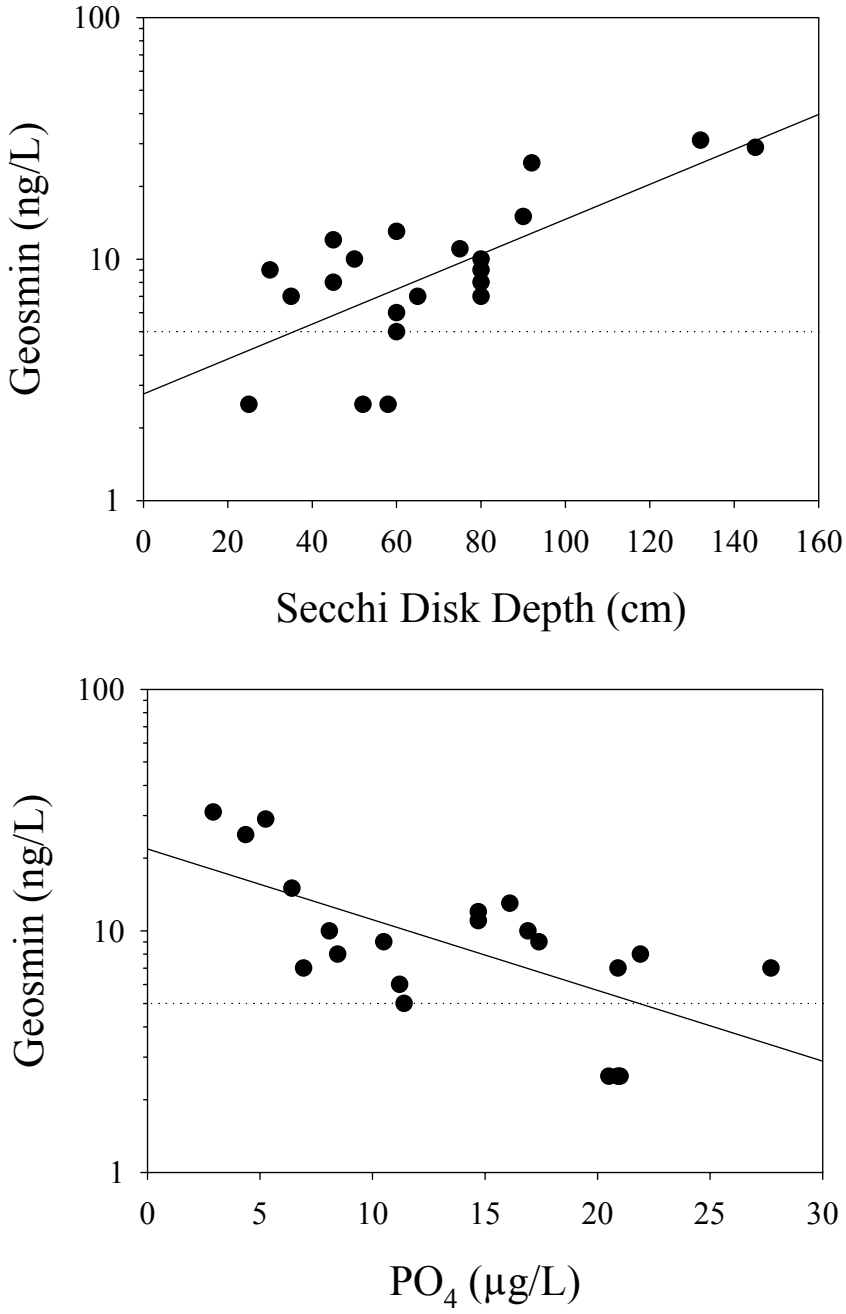


Figure 16. Significant regression relationship between Secchi Disk depth and geosmin and PO_4 and geosmin in Clinton. Horizontal line corresponds with geosmin concentrations of 5 ng/L. See text for regression equations and r^2 values (Equations 6 and 7).

A three-variable model that explained 82% of the variation in geosmin concentrations was also developed for Clinton:

(8) $\log(GEOS) = 1.38 + 1.78(TN) - 1.45 \log(TEMP) + 0.01(\%CYAN)$, $r^2=0.82$

where TN is total nitrogen, TEMP is temperature, and %CYAN is the percent of cyanobacterial biovolume.

CheneyLake

We were unable to develop significant regression models for predicting geosmin concentrations using the data collected from Cheney (all models $P>0.05$).

Marion Reservoir

A single-variable regression model was developed for Marion that explained 33% of the variation in geosmin (GEOS) concentrations (Figure 17):

(9) $\log(GEOS) = 0.88 + 0.28 \log(TOTCYA)$, $r^2=0.33$

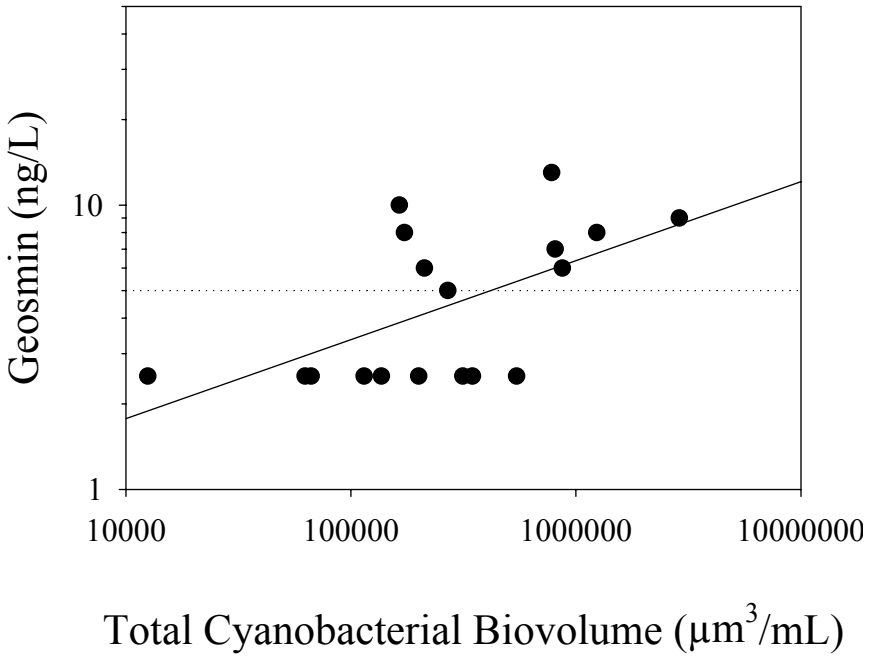
where TOTCYA is total cyanobacterial biovolume. A second single variable model was developed for Marion that explained 30% of the variation in geosmin (GEOS) concentrations (Figure 17):

(10) $\log(GEOS) = 2.69 - 1.14 \log(PO_4)$, $r^2=0.30$

A three-variable model that explained 72% of the variation in geosmin concentrations was also developed for Marion:

(11) $\log(GEOS) = -10.7 + 0.98(pH) + 0.012(SECC) + 0.44 \log(TOTCYA)$, $r^2=0.72$

where SECC is Secchi Disk depth and TOTCYA is total blue-green biomass.



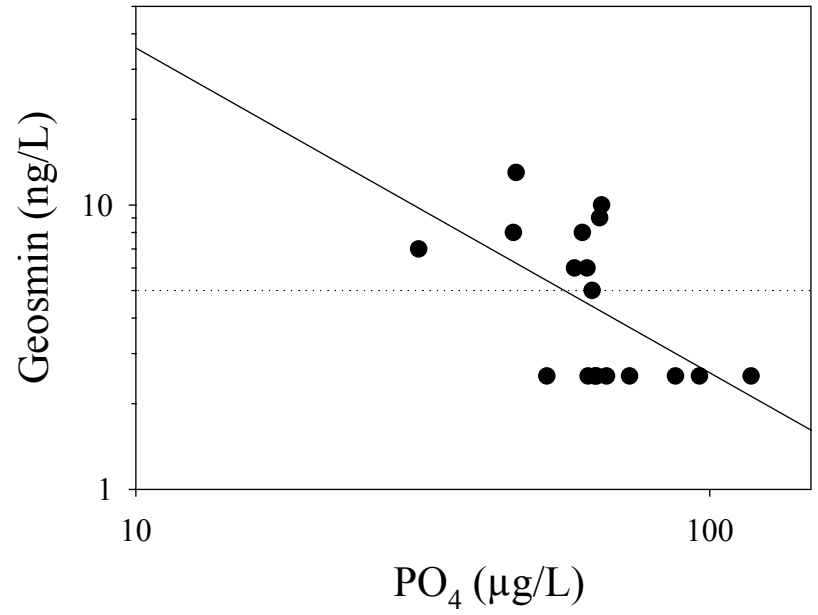


Figure 17. Significant regression relationship between Total Cyanobacterial Biovolume and geosmin and PO_4 and geosmin in Marion. Horizontal line corresponds with geosmin concentrations of 5 ng/L. See text for regression equations and r^2 values (Equations 9 and 10).

United States Army Corps of Engineers Dataset

The occurrence of taste and odor events (geosmin >5 ng/L) were much less frequent in the USACE samples than were observed in the samples collected for the majority of the study reservoirs. For example, geosmin concentrations greater then 5 ng/L were only observed in 18% (7 out of 39) the USACE samples. In general, the inclusion of the USACE data reduced the significance of the predictive models that were originally obtained using the KBS data set alone. Furthermore, we were unable to develop any models that could be used to significantly ($P<0.05$) predict geosmin concentrations using the USACE data set alone.

Discussion and Conclusions

Taste and odor events impact drinking water reservoirs throughout Kansas (e.g. Arruda and Fromm, 1989; Smith *et al.*, 2000; Wang *et al.*, 2005; Christensen *et al.*, 2006). Because treatment costs can be high, it is not practical to continuously treat water for taste and odor control. Instead, predictive tools are needed that allow water treatment managers to determine when taste and odor events are most likely to occur to help make treatment decisions. The purpose of this study was to develop a series of relatively simple models for predicting the occurrence of geosmin concentrations using data collected from several eastern Kansas reservoirs.

Spatial and Temporal Trends in Geosmin

In general, there was little spatial variation in geosmin concentrations on individual sampling dates within each reservoir (Figure 12). These results suggest that geosmin production did not result from localized processes that were limited to specific regions of the reservoirs (i.e., periphyton production in the shallower branches of a reservoir). Instead, geosmin concentrations tended to be relatively similar at the three sampling sites on any given date, indicating that geosmin was either being produced throughout the reservoirs or that it was produced at localized sites and then diffused rapidly throughout the reservoirs. The one exception to this was Marion, where we

collected additional samples in July and September directly from surface algal blooms in the riverine and transition zones. These samples had geosmin concentrations that were higher than the concentrations at the three sampling sites on the same sample date (Figure 12). It should also be noted that we might have missed surface blooms in some of the reservoirs that occurred between our sampling events. For example, there was a bloom at Cheney that dissipated shortly before we sampled in July (J. Graham, USGS, personal communication).

Geosmin concentrations varied temporally within some of the reservoirs. Big Hill experienced episodic increases in geosmin concentrations in the early summer and winter, while Clinton experienced its greatest increases in the winter. Winter increases in geosmin concentrations have been observed in both of these reservoirs in the past (Sam Atherton, PWWSO#4, personal communication and Wang *et al.*, 2005). As mentioned above, Marion experienced episodic increases in geosmin concentrations in July and September. In contrast, geosmin concentrations were around 10 ng/L throughout the study in Cheney, suggesting that the potential for taste and odor events was high throughout the summer and into the fall in this reservoir.

Universal Models

Universal reservoir models for predicting geosmin concentrations were developed using data combined from the four reservoirs. A single-variable model explaining 36% of the variation in geosmin concentrations (Equation 1,Figure 14) and a three-variable model explaining 53% of the variation in geosmin concentrations (Equation 2) were developed for the reservoirs. From an ecological perspective these models explained relatively high percentages of variation in geosmin concentrations considering that data was collected from multiple reservoirs, and multiple sampling sites and dates within each reservoir. From a treatment perspective, however, these models may not provide enough explanatory power to make management decisions. Instead, individual reservoir models, which tended to explain a greater percentage of the variation in geosmin concentrations

than the universal models, may be needed. Alternatively, it is also possible that better predictive models could be developed for groups of reservoirs that exhibit similar characteristics such as size, depth, and trophic state; however, more data from a greater variety of reservoirs is needed to develop such reservoir type models.

One variable, PO_4, was a significant predictor of geosmin concentrations in several of the models. Specifically, geosmin concentrations tended to decrease as PO_4 concentrations increased (e.g. Figure 14). These results appear to contradict ecological theory as increases in dissolved nutrient concentrations often results in increases in algal biomass and presumably geosmin production. However, there are several mechanisms that may help to explain this negative relationship between PO_4 and geosmin. First, it is possible that cyanobacteria actually depleted PO_4 concentrations as they increased in biomass (e.g. Wang *et al.*, 1999) resulting in subsequent blooms and increases in geosmin concentrations. Second, as phosphorus concentrations decreased, PO_4 may have become limiting. Under P-limiting conditions, algal cells may have extra nitrogen that they can in turn use to produce N-rich geosmin (V.H. Smith, University of Kansas, personal communication). Regardless of the mechanisms, it is important to note that PO_4 was consistently an important predictor of geosmin concentrations and changes in PO_4 concentrations may play an important role in early warning systems in drinking water reservoirs.

Individual Reservoir Models

Big Hill

The models developed for Big Hill had greater predictive power (higher r^2 values) than the models developed for the other three reservoirs. As mentioned earlier, Big Hill generally had lower nutrient and chlorophyll *a* concentrations than the other reservoirs (Table 3). Therefore, our results suggest that it may be more difficult to develop predictive models for eutrophic reservoirs than it is for mesotrophic reservoirs such as Big Hill. Furthermore, our results suggest that Kansas reservoirs

with relatively low concentrations of nutrients and chlorophyll are also vulnerable to taste and odor events.

In particular, the percent biovolume of *Aphanizomenon* was a very good predictor of geosmin concentrations in Big Hill (r^2=0.87, Equation 3,Figure 15) suggesting that *Aphanizomenon* is the cause of taste and odor events in this reservoir. Therefore, water treatment personnel could use changes in *Aphanizomenon* biovolume in Big Hill as an early warning indicator of taste and odor events. Cyanobacterial communities in Kansas reservoirs tend to be dominated by only a few taxa that vary considerably in their morphological characteristics (F. deNoyelles, personal communication). Water treatment personnel from Big Hill could learn to coarsely identify cyanobacteria and collect water samples at regular intervals to monitor changes in algal community dynamics. Several treatment facilities including the cities of Tulsa, OK (Ray West, City of Tulsa, personal communication), and Springfield, MO (David Ballou, City of Springfield, personal communication) currently use similar procedures to monitor cyanobacteria as early warning indicators. Conversely, fluorometers (Figure 13) could be used to monitor changes in phycocyanin concentrations (cyanobacterial pigments) over time (e.g., Izydorczyk *et al.*, 2005; Gregor *et al.*, 2007). However, it is important to note that fluorometers such as the ones used in this study provide relative phycocyanin concentrations and do not distinguish between cyanobacterial taxa. Therefore, more detailed algal community data would be needed to determine how relative changes in phycocyanin concentrations obtained from *in-situ* fluorometers correspond to actual changes in algal community dynamics and specific producers of taste and odor compounds.

Clinton

In addition to PO_4 (see discussion above about the negative relationship between geosmin and PO_4), Secchi Disk depth (water clarity) was an important individual predictor of geosmin concentrations in Clinton (r^2=0.50: Equation 6, Figure 16). At low Secchi Disk depths, observed

geosmin concentrations were both above and below human detection limits (5 ng/L); however, at Secchi Disk depths greater than 80 cm, geosmin concentrations were always above human detection limits (Figure 16). Increased water clarity, which often results in greater light availability, has been shown to have positive effects on cyanobacterial production (e.g. Havens *et al.*, 1998). Secchi Disk depths are relatively easy to collect assuming that water treatment personnel can get directly on to a reservoir. However, it is important to stress that low Secchi Disk depths (<80 cm) would have limited predictive power, while high Secchi Disk depths (>80 cm) may be a good indicator of conditions that are suitable for taste and odor events in the reservoir.

Several variables were incorporated in the multiple-variable model for Clinton including total nitrogen, temperature, and total cyanobacterial biovolume (Equation 8). Increases in total nitrogen concentrations often result in increases in cyanobacterial biovolume (Downing *et al.*, 1999). Interestingly, there was a negative relationship between temperature and geosmin. While temperature may not be the best variable to include in water quality variables because reservoirs can experience diel variation (Andy Ziegler, USGS, personal communication), we have included it the model because we believe that it reflects seasonal changes in temperature. Taste and odor events commonly occur in the winter in Clinton when water temperatures are lower (Wang *et al.* 2005). Total cyanobacterial biovolume was also an important variable that could be used as an early warning indicator as described above for *Aphanizomenon* biomass in Big Hill.

Cheney

While we were unable to develop models for predicting geosmin concentrations with the water quality data that we collected from Cheney, several previous studies have presented significant models for predicting geosmin in Cheney. Smith *et al.* (2002) presented a one-variable model that explained 72% of the variation in geosmin concentrations:

(12) Geosmin = -1.08 + 0.412(CHL), r^2=0.72

where CHL is chlorophyll *a*. In their study, Smith *et al.* (2002) used average water quality data that was collected from 6 reservoir sites over a period of 15 months. Christensen *et al.* (2006) also developed a model with two variables that explained 71% of the variation in geosmin concentrations:

(13) $\log(GEOS) = 7.23 - 1.06 \log(TURB) + 0.0097(SPCON), r^2=0.71$

where TURB is turbidity and SPCON is specific conductance. A unique aspect of the model present by Christensen *et al.* (2002) is that it is based on real-time data that can be accessed from remote locations to predict taste and odor events. It is important to point out that the models of Smith *et al.* (2002) and Christensen *et al.* (2006) identified different variables as significant predictors of geosmin concentrations for the same reservoir suggesting that relationships between geosmin and water quality variables can be highly variable over time within individual reservoirs. Therefore, multiple years of data is likely needed to incorporate longer temporal patterns in to more accurate predictive models.

Gardner

Predictive models were not developed for Gardner because taste and odor events were not observed in the reservoir – geosmin concentrations only exceeded 5 ng/L in only one sample (Figure 12). However, it is important to point out that Gardner is a eutrophic reservoir with average total phosphorus and total nitrogen concentrations of 78.8 µg/L and 800 µg/L respectively (Table 3). Gardner also had average chlorophyll concentrations that were greater than the average concentrations in all of the reservoirs except Cheney; however, these high levels of chlorophyll were not associated with the production of geosmin. The lack of taste and odor events in Gardner, combined with the presence of taste and odor events in the mesotrophic Big Hill, suggest that trophic state alone is not a good indicator of taste and odor events in Kansas reservoirs.

Marion

Total cyanobacterial biovolume was a reasonably good predictor of geosmin concentrations in Marion (r^2=0.33; Equation 9; Figure 17). When total cyanobacterial biovolume was greater than 1,000,000 μm^3/mL, geosmin concentrations were always above the human detection limit . Therefore, high concentration of total cyanobacterial biovolume (threshold at 1,000,000 μm^3/mL) may provide an indicator of taste and odor events in Marion. At concentrations below this threshold geosmin concentrations were both above and below human detection limits. Interestingly, Secchi Disk depth was also an important variable in the Marion multiple-variable model suggesting that water clarity may be an important ecological factor influencing taste and odor events (see discussion of Secchi Disk depth in the *Clinton* section).

United States Army Corps of Engineers Dataset

It is important to note that when data collected from additional reservoirs was added to the models, their predictability decreased. Specifically, with the USACE data included in the universal data set, the models were no longer significant. Furthermore, we were unable to develop significant predictive models for the USACE data alone. These results further highlight the difficulty in Figure 17.

Additional Taste and Odor Producers

While cyanobacteria are most often associated with taste and odor events in drinking water reservoirs, there are also a number of additional microorganisms such as Actionomycetes that produce geosmin and potentially contribute to taste and odor events (e.g. Lanciotti *et al.*, 2003; Nielsen *et al.*, 2005). For example, Mau *et al.* (2004) suggested that Actinomyctes were responsible for at least some taste and odor events in Lake Olathe, KS. Because of their potential importance, Actinomycete data should be included in any additional research or attempt to develop predictive models in Kansas reservoirs to help determine what role they play in taste and odor events.

Model Verification and Implementation

Although we were able to develop several significant models for predicting geosmin concentrations, it is important to stress that the models presented in this report have not been tested and their accuracy in predicting actual taste and odor events is unknown. Furthermore, it is unknown how applicable these models are to additional reservoirs not used in the current study. Therefore, the accuracy of these models need to be tested in at least the four study reservoirs before they can be used or implemented in a second phase of this research. Additional data collected during a Phase II could also be used to refine the models to increase their predictive power.

Once the models are tested and refined they can be implemented, and several factors should be considered when implementing specific models. First, the variables included in implemented models must be easy to collect in order to encourage use by treatment personnel. Second, the data acquisition time must be rapid (1-5 days at the most) for the models to be effective at predicting taste and odor events in a time frame that allows for management decisions to be made. Third, models should be selected that include variables that are relatively inexpensive to collect so that a number of samples can be collected throughout the year at regular intervals. Reservoir specific research is needed to determine how often samples need to be collected so that they can be effectively used in predictive models. 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. Since models have been developed using reservoir samples, additional research is needed to determine if models can be used on raw water samples as well.

2. Watershed Models

Introduction

Watershed conditions can play an important role in determining water quality that in turn impacts the ecological health of ecosystems dependent upon that water. It has been observed that

watersheds are large-scale systems that limit the dynamic processes of subsystems within them such as grasslands, forests, etc. (Kepner ,1995). Furthermore, the amount and spatial arrangement of land cover types in the watershed are related to ecological processes and to the effect a specific stress may have on a resource within a region, such as fisheries health. Thus, watershed characterization is an essential component for determining the status and trends in the condition of ecological resources (Norton and Slonecker 1990). Previous work has demonstrated that water quality is influenced by watershed composition and pattern (Sponseller *et al.*, 2001; Herlihy, 1998; Hunsaker *et al.,* 1992; Hunsaker *et al.* 1995). Watershed attributes have also been examined to determine their relative contribution to nonpoint source pollution (Whistler, 1996; Haith ,1976). Typically, these studies have been limited in scope to small and medium watersheds (<10,000 hectares) and have utilized land use and land cover information from aerial photographs or satellite imagery. Sponseller *et al.* (2001), Jones et al 2001) and Detenbeck *et al.* (2000) recognized and recommended that future watershed studies incorporate the unique ability of time series remotely sensed imagery to provide data on changes in vegetation structure, composition, and land surface condition.

The normalized difference vegetation index (NDVI) is a well-established and commonly used vegetation index in studies utilizing remote sensing data because it is roughly correlated with green plant biomass and vegetation cover (Box *et al.*, 1989; Tucker, 1979). The NDVI is based on the relative reflectance values in the red and near infrared (NIR) wavelengths: NDVI = (NIR - Red)/(NIR + Red). Jones *et al.* (1996) evaluated the potential of NDVI to assess watershed health and hypothesized it could indicate losses in productivity, increased erosion, and losses of the vegetative buffer capacity along riparian corridors. They suggested examining NDVI patterns and change, as well as comparing observed versus expected NDVI based on soils, topography, vegetation and climate. Whistler (1996) explored NDVI values derived from Landsat Multi-

Spectral Scanner (MSS) imagery as a surrogate for biomass, and hypothesized that NDVI values would have stronger relationships with water chemistry parameters than with land cover proportions derived from the same imagery. He found significant relationships between NDVI and selected water quality parameters that, in fact, were stronger than relationships to land use/land cover in most cases. In an earlier study, the Kansas Biological Survey and EPA Region VII partnered to explore watershed-water quality relationships. NDVI or VPMs were more highly correlated to the selected stream condition parameters than land use/land cover proportions. A major conclusion derived from this work was that NDVI or VPMs better explain variation in water quality conditions than land use/land cover composition (Griffith *et al.*, 2002; Martinko *et al.*, 2000; Griffith, 2000; Whistler, 1996). The purpose of this section of the study was to explore relationships between NDVI or VPMs and geosmin concentrations to determine if predictive watershed models could be developed for drinking water reservoirs.

Method

Water quality/taste-and-odor data

Significant challenges to this element of the project were the limitations of the water quality datasets. The ideal data set for developing relationships between seasonally-varying satellite-derived measures of watershed conditions and reservoir water quality conditions would be weekly, biweekly, or even monthly measurements of water quality parameters for a suite of reservoirs. This study sampled four reservoirs (Big Hill Reservoir, Marion Reservoir, Clinton Lake, and Cheney Reservoir) multiple times during the single project year (2006), and also acquired existing water quality data for multiple reservoirs in Kansas, Missouri, and Oklahoma. As such, the available data set is incomplete spatially (insufficient number of reservoirs sampled), thematically (different water quality parameters collected for different reservoirs), and chronologically (few long-term/multi-year data sets exist).

The most complete data set for this element was the geosmin database for Eucha Reservoir in Oklahoma, spanning one partial year (1999) and four complete years (2000-2003, inclusive). Spavinaw Reservoir also had a geosmin database for the same period, but Eucha Lake drains into Spavinaw, and thus the Eucha watershed shares much of the Spavinaw watershed. The Eucha dataset contains geosmin and MIB levels (ng/L) sampled approximately biweekly during the period August 31, 1999 through December 31, 2003 (Figure 18). Temporal sampling density was apparently increased during certain periods during the year. Data were aggregated to monthly values to reduce these irregularities in sampling density, with a typical monthly value representing between 1 and 8 samples for that month .

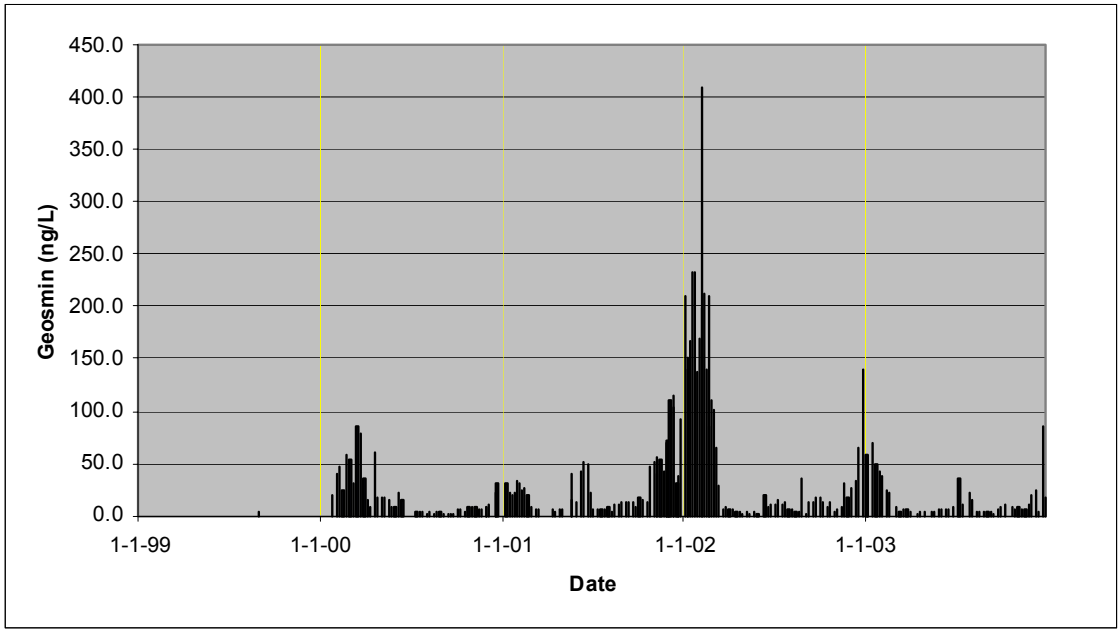


Figure 18. Geosmin concentrations for Eucha Reservoir, Oklahoma, during 1999-2003.

Table 4. Geosmin and MIB data from Eucha Reservoir, Oklahoma, during 1999-2003

Sampling Date	Geosmin (ng/L)	MIB (ng/L)		Sampling Date	Geosmin (ng/L)	MIB (ng/L)
Aug-99	4.50	0.00		Jan-02	179.75	2.11
Oct-99	0.00	0.00		Feb-02	183.26	1.08
Dec-99	0.00	0.00		Mar-02	27.65	0.92
Jan-00	19.00	0.00		Apr-02	4.08	1.18
Feb-00	44.80	0.00		May-02	3.09	1.11
Mar-00	57.75	0.00		Jun-02	13.18	4.45
Apr-00	25.40	0.45		Jul-02	10.72	4.68
May-00	13.26	0.00		Aug-02	12.17	6.71
Jun-00	9.50	2.48		Sep-02	12.26	17.75
Jul-00	3.13	3.28		Oct-02	9.30	12.30
Aug-00	3.33	5.15		Nov-02	15.56	4.17
Sep-00	1.78	3.23		Dec-02	66.55	2.20
Oct-00	6.48	14.18		Jan-03	50.92	1.38
Nov-00	7.24	7.16		Feb-03	28.37	1.47
Dec-00	21.00	1.90		Mar-03	5.44	0.53
Jan-01	26.00	2.02		Apr-03	2.10	1.51
Feb-01	21.68	1.74		May-03	3.45	1.37
Mar-01	6.80	1.35		Jun-03	6.57	0.77
Apr-01	4.33	0.84		Jul-03	22.47	4.99
May-01	18.20	1.84		Aug-03	6.54	6.03
Jun-01	41.35	4.21		Sep-03	4.30	27.00
Jul-01	5.87	2.30		Oct-03	8.17	44.37
Aug-01	8.73	4.02		Nov-03	7.76	23.44
Sep-01	12.16	15.63		Dec-03	29.65	3.74
Oct-01	28.70	10.04				
Nov-01	55.47	5.37				
Dec-01	81.35	1.88				

Satellite data

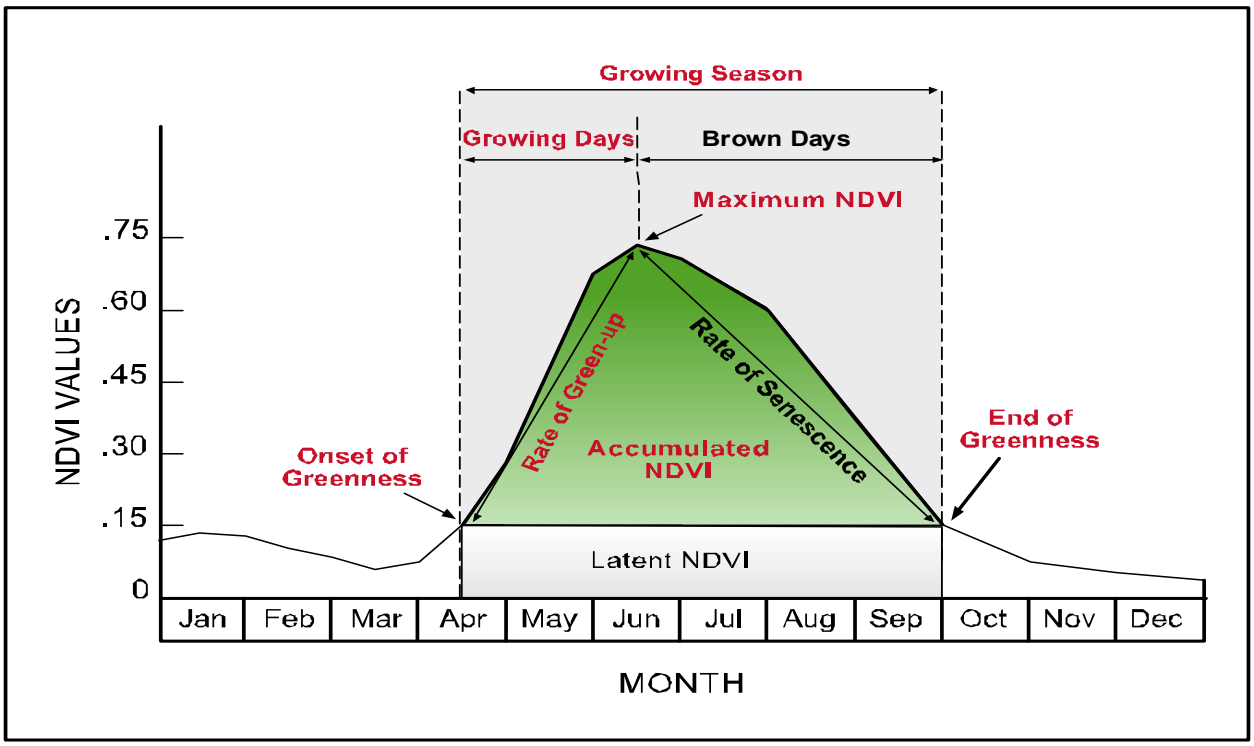
NOAA-AVHRR NDVI biweekly composite images for 1989-2006 have been acquired on an ongoing basis by KARS from the USGS EROS Data Center in Sioux Falls, SD. Each biweekly composite consists of the maximum NDVI value within each two-week period for each pixel (Eidenshink, 1992), for a total of 26 images per year. Vegetation index data are rescaled by EROS during processing from a range of -1.0 to +1.0, to 0 to 200. Values less than 100 typically represent snow, ice, water, and other non-vegetated earth surfaces. Vegetation phenology metrics described

by Reed *et al.* (1994) were generated from the NDVI time series for each year are included in Figure 19.

Results

Watershed Boundary Dataset (WBD) hydrologic unit geospatial data in the form of shapefiles were downloaded off the USDA Geospatial Data Gateway. This dataset at 1:24,000 scale is an expanded version of the hydrologic units created in the mid-1970's by the U.S. Geological Survey under the sponsorship of the Water Resources Council. The WBD is a complete set of hydrologic units from new watershed and sub-watersheds less than 10,000 acres to entire river systems draining large hydrologic unit regions, all attributed by a standard nomenclature. Polygons for the Eucha watershed were extracted from the more extensive WBD dataset and dissolved on the HUC-10 code to create a watershed boundary mask. Mean, standard deviation, minimum, and maximum values for all VPM metrics were computed using all pixels falling within the Eucha watershed boundary (Figure 19).

VPM and geosmin data were analyzed using SPSS. The low number of samples (n=5) substantially limited statistical analysis. With one exception, no significant correlations were found between VPM watershed metrics and geosmin levels for Eucha Lake. One statistically significant negative correlation was observed between December geosmin levels and the mean watershed rescaled maximum greenness (NDVI). A regression equation between the two parameters was developed with an r^2 value of 0.97 (Figure 20).



Metric	Ecological Function or Process Represented
Date of onset of greenness	Beginning of photosynthetic activity
Date of end of greenness	End of photosynthetic activity
Duration of greenness	Length of photosynthetic activity
Date of maximum greenness	Time when photosynthesis is at maximum
Growing days	Number of days from onset of greenness to maximum NDVI
Growing season	Number of days from onset to end of greenness
Value of onset of greenness	Level of photosynthesis at start
Value of end of greenness	Level of photosynthesis at end
Value of maximum NDVI	Level of photosynthesis at maximum
Range of NDVI	Range of measurable photosynthesis
Accumulated NDVI	Net primary production
Rate of green up	Acceleration of increasing photosynthesis
Rate of senescence	Acceleration of decreasing photosynthesis
Mean daily NDVI	Mean daily photosynthesis activity

Figure 19. Vegetation phenology metrics described by Reed *et al.* (1994) that were generated from the NDVI time series for each year are included in the data set from Eucha Reservoir.

Table 5. Vegetation phenological metrics data for the Eucha Watershed, 1998-2003.

		1998	1999	2000	2001	2002	2003
Accumulated (summed) growing season NDVI	min	673.00	791.00	881.00	727.00	792.00	1103.00
	max	1360.00	1417.00	1403.00	1365.00	1163.00	1363.00
	mean	1160.24	1256.41	1149.45	1158.06	1025.01	1252.60
	s.d.	129.78	105.22	104.41	80.64	71.35	49.32
Average growing season NDVI	min	158.60	159.05	158.42	156.83	155.75	159.16
	max	175.69	174.94	176.20	177.06	175.80	177.12
	mean	166.72	165.83	166.90	165.53	164.78	167.92
	s.d.	3.14	2.85	2.94	3.71	3.56	3.25
Rate of senescence	min	0.27	0.50	1.00	0.36	1.78	0.08
	max	8.00	4.50	5.60	8.33	14.50	22.00
	mean	1.96	2.25	2.58	2.22	2.88	5.74
	s.d.	1.31	0.69	0.74	1.35	1.01	3.46
NDVI value at period of dormancy onset	min	145.00	141.00	141.00	144.00	136.00	142.00
	max	173.00	174.00	168.00	169.00	160.00	174.00
	mean	159.94	153.52	153.12	157.77	146.78	153.94
	s.d.	6.09	6.77	6.42	5.66	4.55	4.90
Dormancy onset period	min	15.00	18.00	17.00	16.00	18.00	21.00
	max	24.00	24.00	24.00	23.00	24.00	23.00
	mean	22.30	22.38	21.20	22.49	22.18	22.97
	s.d.	1.96	1.41	1.71	0.71	1.13	0.23
Rate of greenup	min	1.31	2.73	2.09	2.13	2.58	1.80
	max	17.00	16.00	13.00	18.67	32.00	13.50
	mean	5.63	5.95	5.65	6.21	8.60	4.36
	s.d.	2.13	2.57	2.21	2.36	3.39	2.24
Date of maximum greenup (period number)	min	8.00	9.00	9.00	9.00	9.00	8.00
	max	21.00	14.00	16.00	21.00	20.00	22.00
	mean	11.57	10.34	11.05	12.75	11.13	16.37
	s.d.	2.37	1.13	1.17	2.37	1.41	4.26
NDVI value at maximum greenup	min	168.00	170.00	171.00	168.00	166.00	171.00
	max	186.00	186.00	186.00	189.00	185.00	186.00
	mean	178.25	180.25	179.16	177.02	177.54	178.56
	s.d.	3.57	2.75	3.07	4.20	2.87	3.05
Date of greenup onset (period number)	min	4.00	3.00	3.00	4.00	6.00	4.00
	max	8.00	8.00	8.00	7.00	8.00	7.00
	mean	5.90	4.24	4.98	5.80	7.33	5.50
	s.d.	0.96	1.56	1.50	0.95	0.77	0.85
NDVI value at onset of greenup	min	139.00	135.00	135.00	123.00	133.00	130.00
	max	158.00	158.00	157.00	146.00	160.00	150.00
	mean	149.77	147.52	148.08	138.75	147.73	140.81
	s.d.	3.97	4.76	3.68	3.56	5.41	3.84

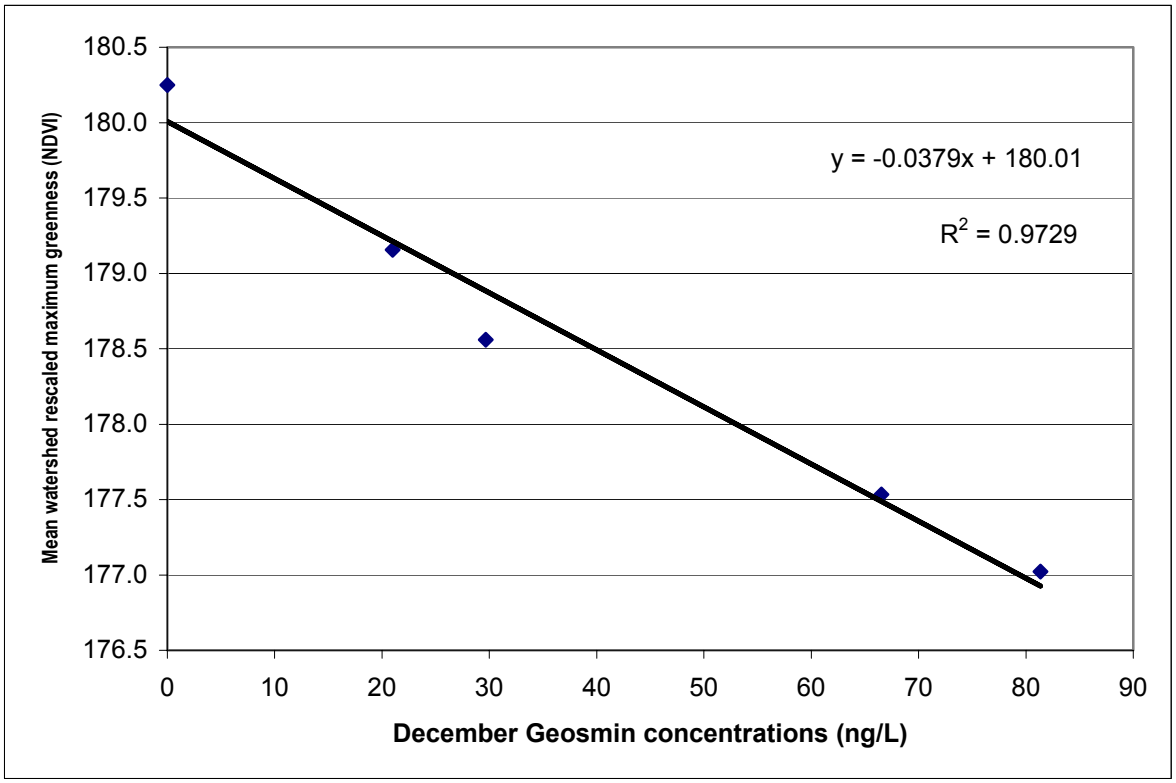


Figure 20. Significant regression relationship between December geosmin concentration and mean watershed the mean watershed rescaled maximum greenness (NDVI) for Eucha Reservoir, Oklahoma, during 1999-2003.

Discussion and Conclusions

Is the relationship between December geosmin concentrations and mean watershed maximum greenness a statistical artifact or an actual environmental relationship? The low number of samples (n=5) argues on the side of statistical artifact, a random relationship purely by chance. Acknowledging this, and setting this aside for the moment for the sake of argument, if we presume the possibility of the validity of the relationship, are there other data sets that might also show similar trends that echo the VPM-geosmin relationship for this watershed? Since vegetation greenness can be closely related to available moisture in a watershed, precipitation records might show similar trends. Annual precipitation data for the station closest to the Eucha watershed (Tulsa, OK) were obtained from the National Weather Service. Plotted with the dates of each geosmin-VPM observation, annual precipitation shows similar trends. Years of high annual precipitation

(1999, 2000, 2003) were years of high mean watershed maximum greenness and low geosmin, and conversely (Figure 21).

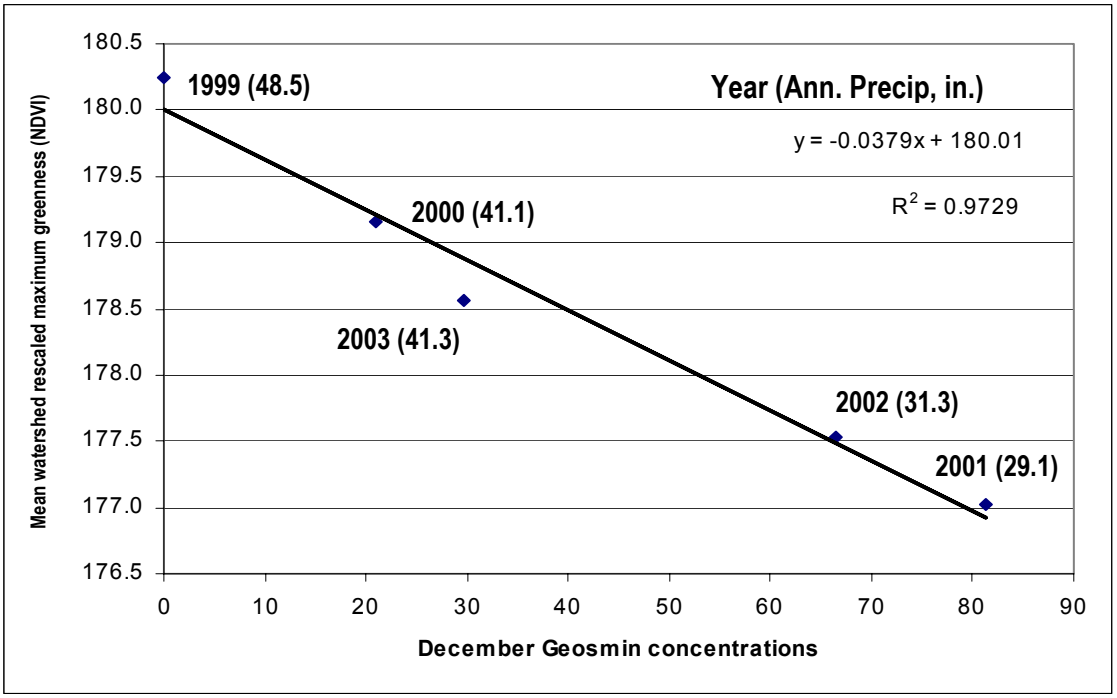


Figure 21. Significant regression relationship between December geosmin concentration and mean watershed the mean watershed rescaled maximum greenness (NDVI) for Eucha Reservoir, Oklahoma, during 1999-2003. Annual precipitation data is included.

What is "mean maximum watershed greenness," and what is it telling us about conditions within the watershed that appear, at least for the sake of argument, to be strongly inversely related to December geosmin concentrations? Translated, the mean maximum watershed greenness metric represents the average NDVI value recorded across a watershed during the biweekly period of peak greenness during a growing season (Figure 22). If vegetation conditions across a watershed are excellent, the NDVI value will be high. If conditions are uniformly poor (perhaps during a drought year), the value will be low. Since the metric averages all the NDVI values across the watershed during this peak period, local high or low variations are damped out and the metric is a measure of the *overall* greenness during the peak.

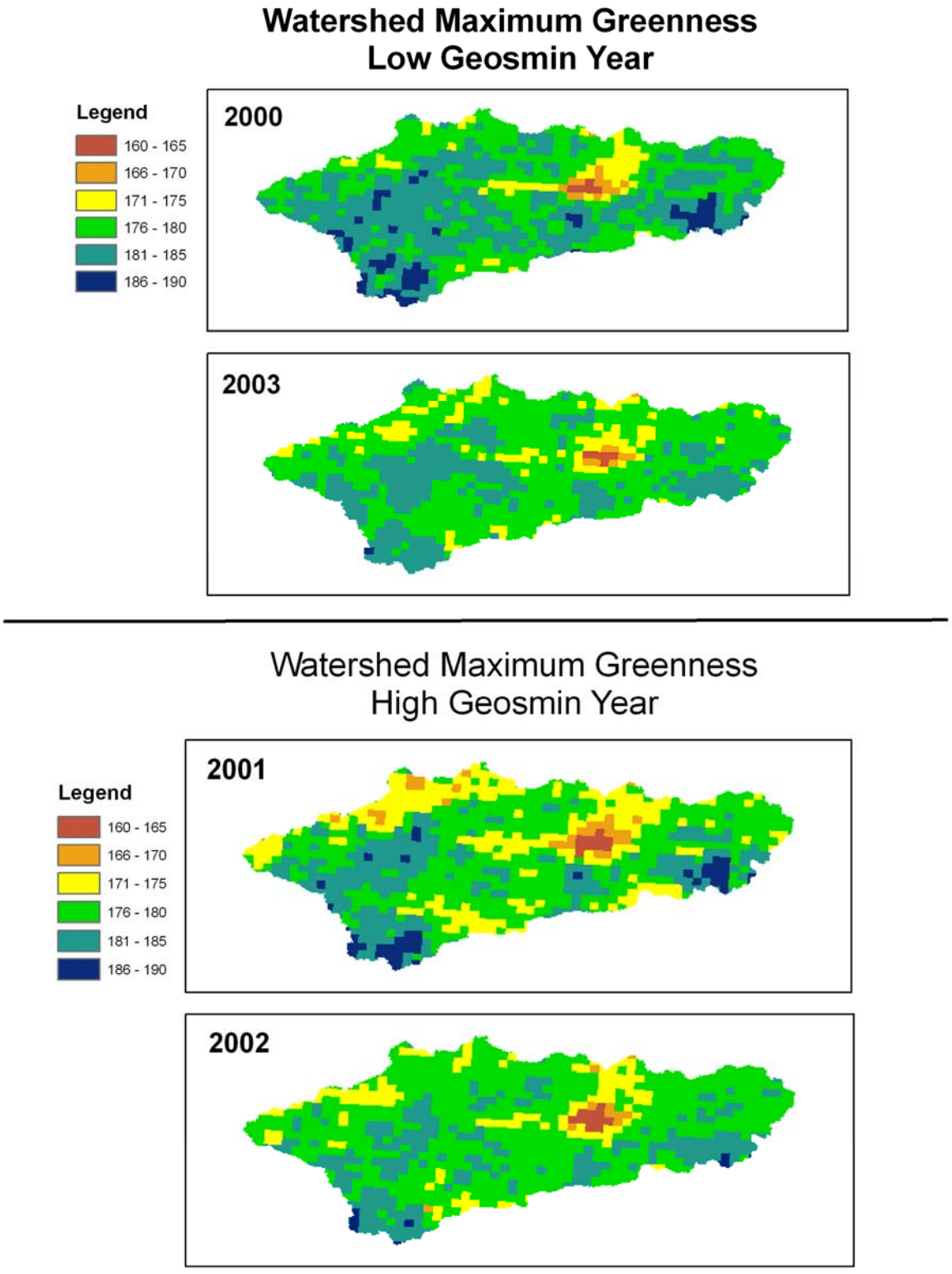


Figure 22. Watershed maximum greenness values for the Eucha Reservoir watershed in years of low (2000, 2003) and high (2001, 2002) geosmin years.

3. MODIS Models

Introduction

Our objective in this section was to use Moderate-resolution Imaging Spectroradiometer (MODIS) data to document changes in water quality from ten KS reservoirs. Based on past experience with using satellite imagery to monitor vegetation greenness and changes in both terrestrial and aquatic conditions, we hypothesized that 16-day composited MODIS Normalized Difference Vegetation Index (NDVI) data might provide an ongoing indication of possible algal blooms within a reservoir.

Methods

Reservoir Selection

Ten reservoirs were selected for this element of the project (Table 6). Big Hill Lake and Gardner Lake were not used, even though they were sampled as part of other project elements, on the basis of size. At the 250-meter spatial resolution of the MODIS NDVI, small lakes do not have sufficient area to provide "water-only" pixels free of influence from non-water areas.

Table 6. Reservoirs used for MODIS project element.

NAME	Area, square kilometers
Cheney Lake	38.99
Clinton Lake	30.63
El Dorado Lake	30.76
Hillsdale Lake	19.73
John Redmond	30.13
Kanopolis Lake	15.29
Marion Lake	24.88
Perry Lake	47.22
Pomona Reservoir	16.87
Tuttle Creek Reservoir	59.55

GIS Data Preprocessing

A polygon shapefile of federal reservoirs was obtained from the Kansas Water Office. Polygon outlines of the ten federal reservoirs listed above were exported to a separate file. A buffer operation was then used to buffer into each lake polygon 250 meters to create a cropped lake perimeter polygon. This buffer operation was performed to ensure that water-only pixels were selected for each lake in the following processes. The polygon shapefile was then converted to 250-meter raster format to create a mask file for application to the MODIS 2006 NDVI composite file (described below).

MODIS Data

The MODIS is a payload scientific instrument launched into Earth orbit by NASA in 1999 on board the Terra (EOS AM) Satellite, and in 2002 on board the Aqua (EOS PM) satellite. Together the instruments image the entire Earth every 1 to 2 days. Terra's orbit around the Earth is timed so that it passes from north to south across the equator in the morning, while Aqua passes south to north over the equator in the afternoon. The instruments capture data in 36 spectral bands ranging in wavelength from 0.4 μm to 14.4 μm and at varying spatial resolutions (2 bands at 250 m, 5 bands at 500 m and 29 bands at 1 km). Red and NIR bands are only ones available at 250m, so that NDVI is available at 250m. MODIS NDVI from either Terra or Aqua are available as time series, in particular non-overlapping 16-day composite tiles (22 composites in 2006).

MODIS NDVI 16-day composites for 2006 were obtained from the EROS Data Center. The MODIS acquires images on a daily basis, but cloud cover often obscures the land surface. In order to produce a cloud-free image of vegetation conditions during a 16-day period, a set of sixteen daily images is used to create a single 16-day composite image. Each NDVI composite consists of the maximum NDVI value within a defined 16-day period for each pixel (Table 7).

Table 7. MODIS NDVI composite periods.

Period	Date Range	Period	Date Range
1	01 Jan 2006 - 16 Jan 2006	12	26 Jun 2006 - 11 Jul 2006
2	17 Jan 2006 - 01 Feb 2006	13	12 Jul 2006 - 27 Jul 2006
3	02 Feb 2006 - 17 Feb 2006	14	28 Jul 2006 - 12 Aug 2006
4	18 Feb 2006 - 05 Mar 2006	15	13 Aug 2006 - 28 Aug 2006
5	06 Mar 2006 - 21 Mar 2006	16	29 Aug 2006 - 13 Sep 2006
6	22 Mar 2006 - 06 Apr 2006	17	14 Sep 2006 - 29 Sep 2006
7	07 Apr 2006 - 22 Apr 2006	18	30 Sep 2006 - 15 Oct 2006
8	23 Apr 2006 - 08 May 2006	19	16 Oct 2006 - 31 Oct 2006
9	09 May 2006 - 24 May 2006	20	01 Nov 2006 - 16 Nov 2006
10	25 May 2006 - 09 Jun 2006	21	17 Nov 2006 - 02 Dec 2006
11	10 Jun 2006 - 25 Jun 2006	22	03 Dec 2006 - 18 Dec 2006

Data Analysis and Display

Because water quality data were not available for all ten reservoirs, particularly data on green and blue-green algae counts, a more qualitative representation of satellite remotely sensed water conditions was performed. Each of the 22 dates of NDVI imagery were density-sliced and color-coded according to a bipolar color progression typically used for depiction of NDVI values.

Results and Conclusion

In all of the following images, low NDVI values that result from low water levels, bare soil, or clear water appear in tones of brown ranging to yellow. Higher NDVI values, which indicate increasing vegetation – usually interpreted as some form of algae, but can also include floating aquatic plants and near-surface submerged aquatic plants – are displayed in tones ranging from green up to dark blue (maximum NDVI, Figure 23 - Figure 25).

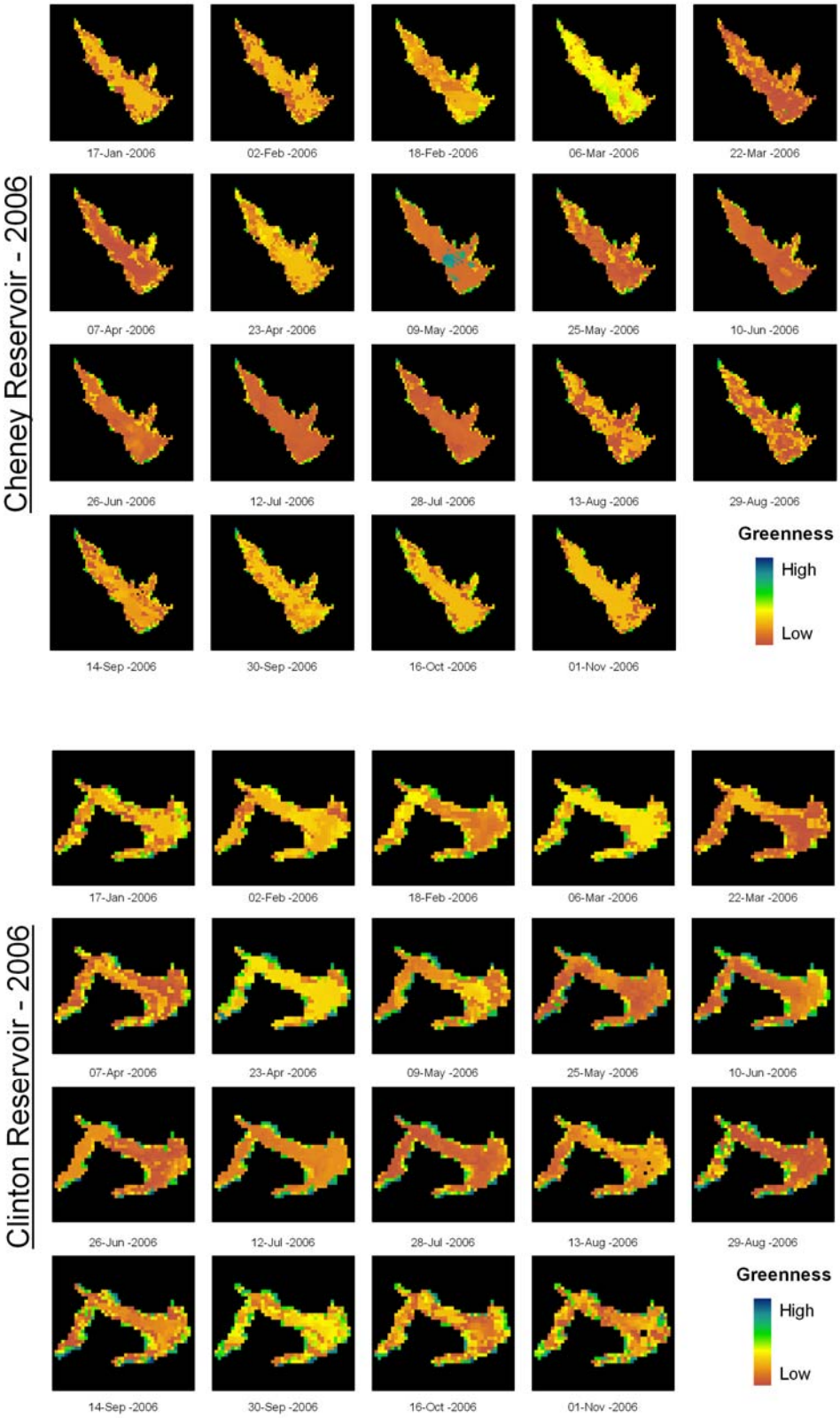


Figure 23. NDVI imagery for study lakes.

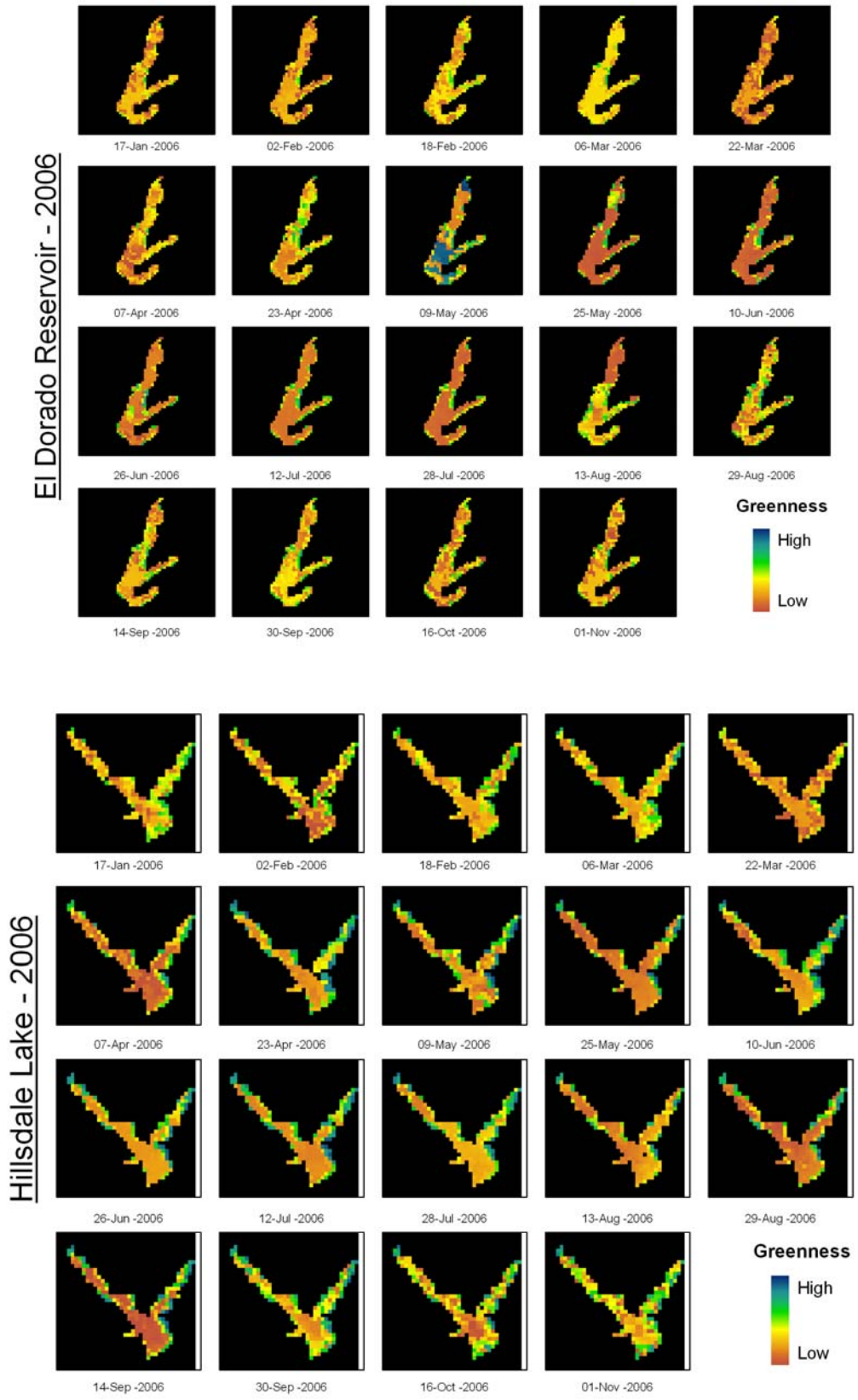


Figure 23. Continued.

Figure 24. Kanopolis Lake in 2006 suffered from severe low water levels in 2006, resulting in the exposure of mud flats in the north end of the lake. As a result, the high NDVI values indicated for the north end of the lake result not from algae blooms, but from weedy vegetation growing on the exposed lake bed. Photos by Mike Rodriquez, Lindsborg, Kansas.

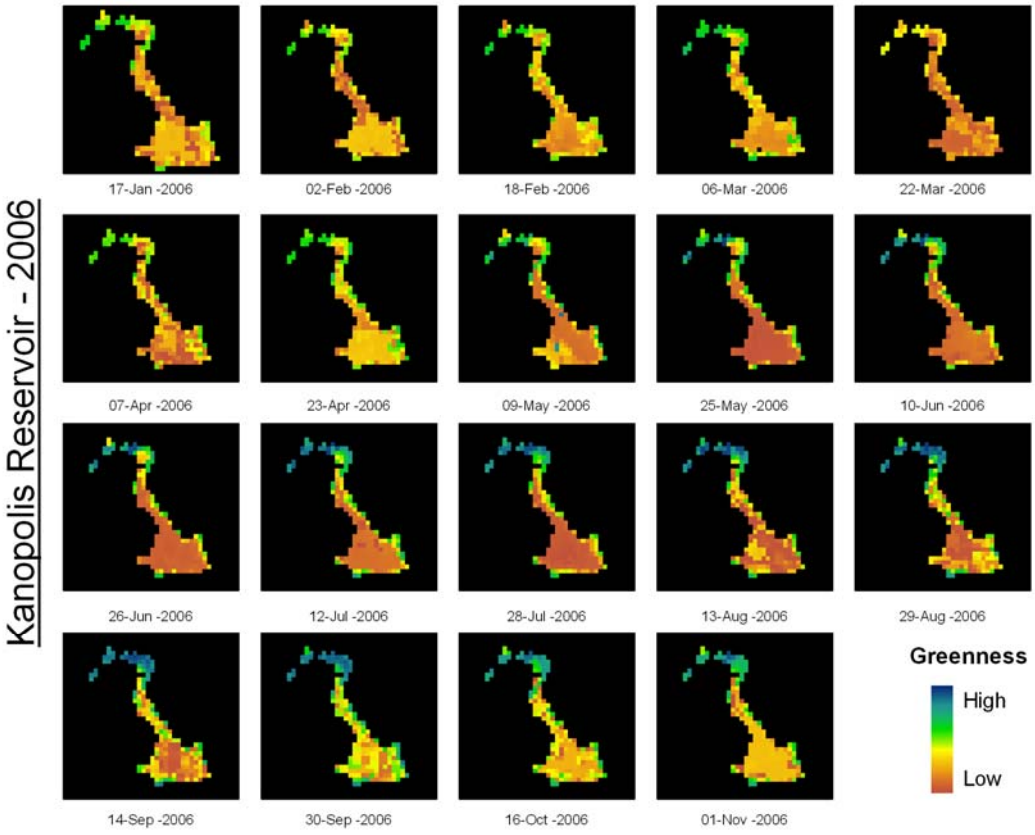
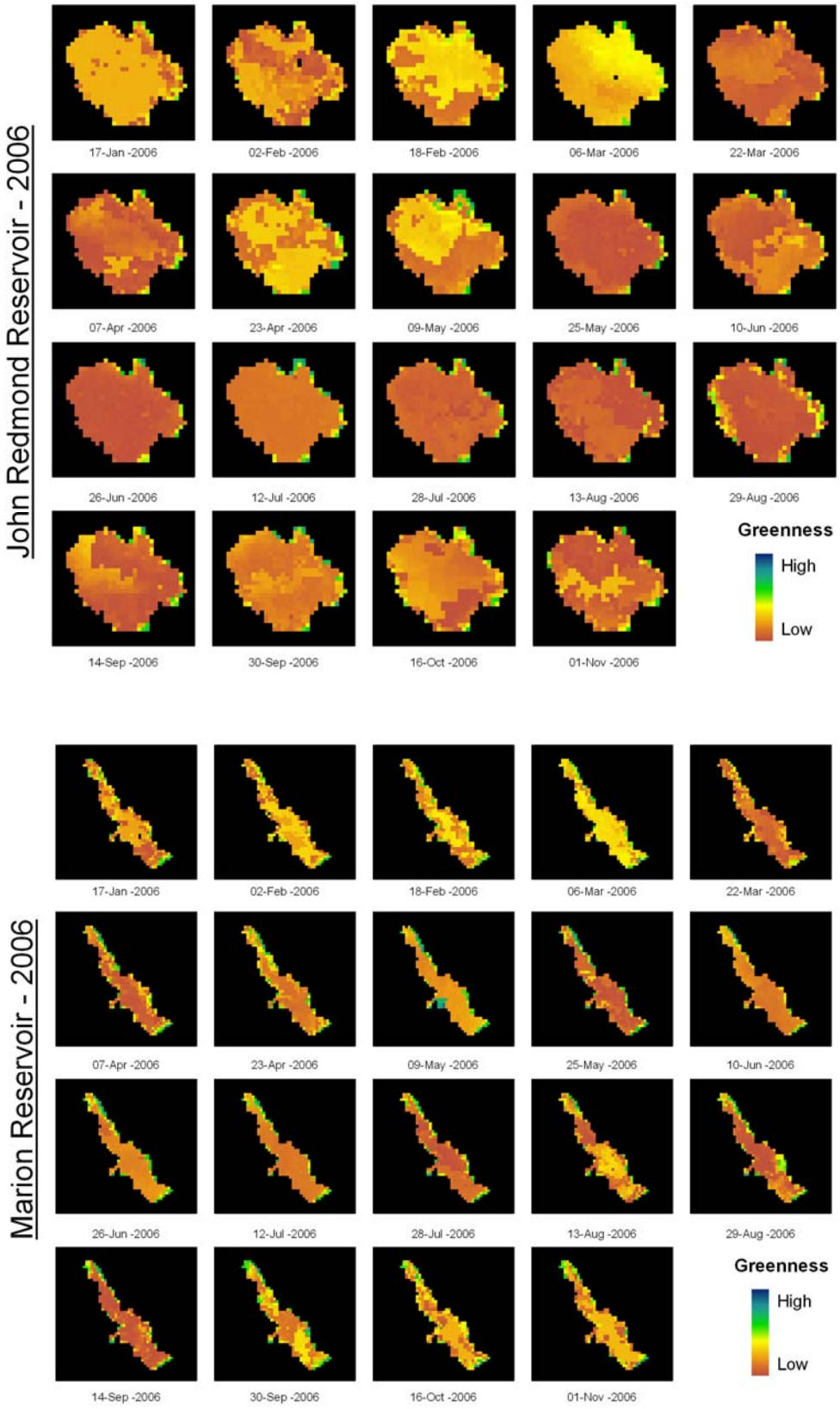


Figure 25. NDVI imagery for study lakes.



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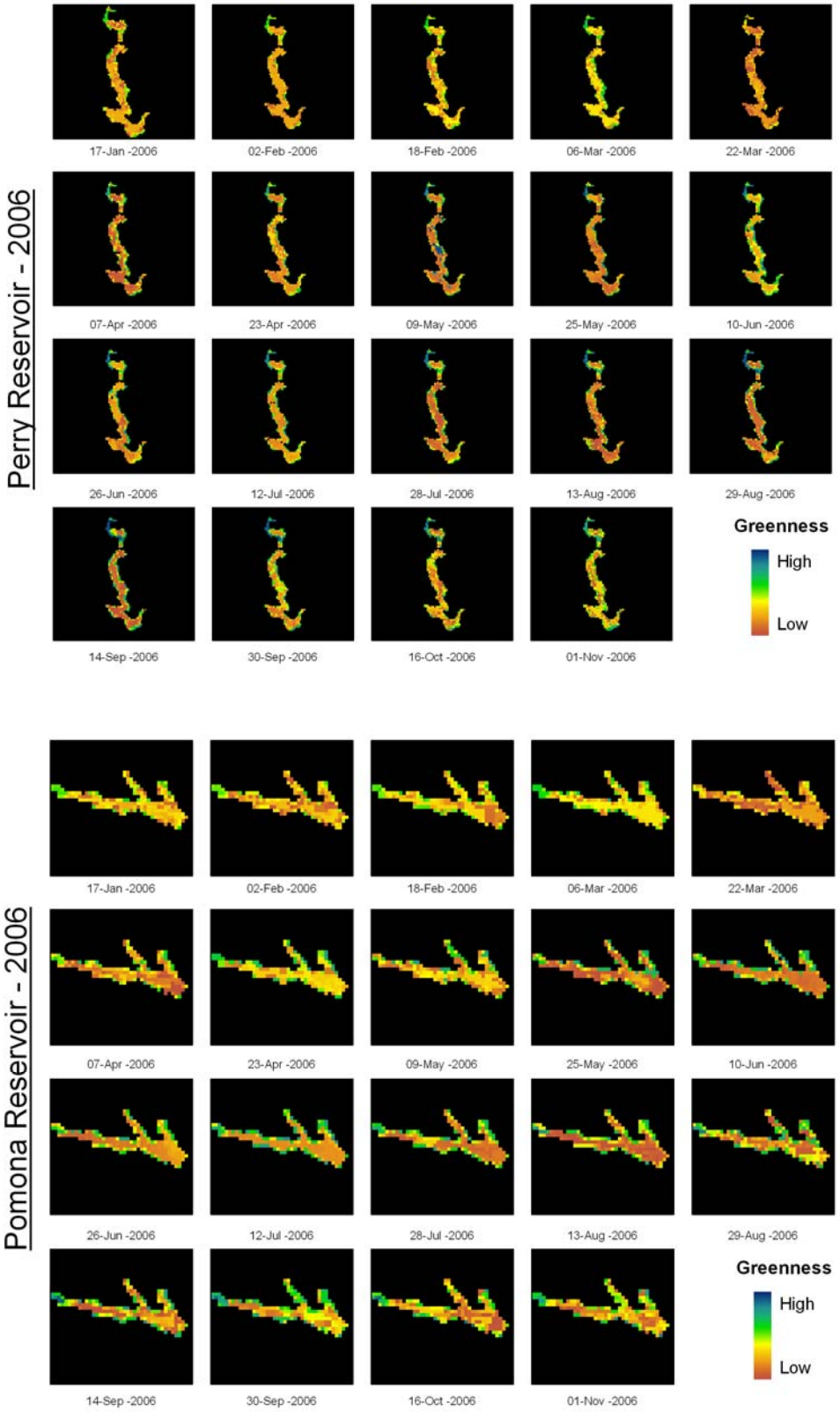

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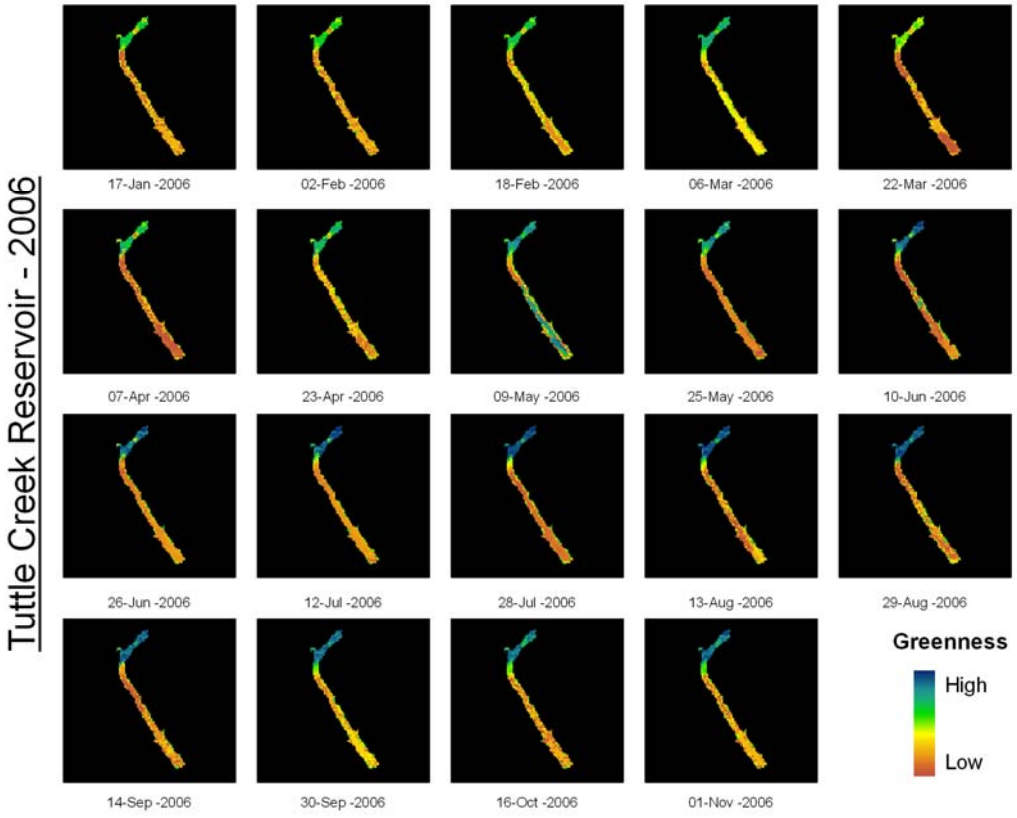

Figure 25. Continued.

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