Spatial and temporal trends in water quality of an irregular, oligotrophic lake: Connections to weather and watershed

Courtesy of Squam Lakes Association

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Abstract

A 35-year record of water quality sampling in the Squam Lakes in New Hampshire was analyzed for spatial and temporal characteristics. Spatial similarities among water quality parameters from 16 monitoring sites were resolved into 5 clusters by the hierarchical Ward Linkage method – Inner/outer Squaw Cove, Inner Dog Cove, Little Squam Lake and Southern stations, NE Stations, and Western Stations. Cluster analysis revealed strong spatial discrimination of groups related to their inherent water quality characteristics. These zones were, for the most part, geographically clustered as well. Time series analysis showed small increases in chlorophyll-a over the 35-year period of record. Chlorophyll-*a* concentrations (Chl-*a*) decreased at four monitoring stations but increased at four ($p<0.05$). Due to this spatial variability, Chl-*a* concentrations cannot be said to have significantly increased or decreased lakewide in Squam Lake. However, the Chl-*a* concentrations in Little Squam Lake exhibited increases of .024 and .057 $\mu g\ L^{-1}\ yr^{-1}$ over the period of record. Spectral analysis of water quality in the Squam Lakes helped to characterize groups of monitoring stations. The group of Little Squam Lake and Southern stations showed high levels of variability around 20 years in Chl-*a* and Secchi Depth (SD) - a cycle observed in the nearby river discharge datasets, a smaller level of variability around 10 years for both parameters, and relatively high variability on the 20+ year time scale for Chl-*a*. At the Northeastern group of stations, SD and Chl-*a* varied on completely different time scales; Chl-*a* variability was dominated by the 15-20 year time-scale, but the same time-scale had the least spectral power in the Secchi depth periodogram. For the Western group of stations, high variability at 10 years was observed for all water quality parameters, along with a high level of low-frequency variability.

Introduction

Environmental monitoring programs are essential for our understanding and management of ecosystems. Before we can recognize and address environmental changes, some idea of baseline and natural variability must be established against which to evaluate deviations. Along with temporal changes, it is important to understand the spatial patterns of water quality in ecosystems in order to direct management efforts. Lake monitoring efforts are often limited to a singular site at the deepest point. It has been suggested that "the number of sampling stations should be the nearest whole number to the log10 of the area of the lake in km2…For lakes with irregular boundaries, it is advisable to conduct preliminary investigations to determine whether and where differences in water quality occur before deciding on the number of stations to establish" (UNEP/WHO 1996). The USGS makes similar recommendations, "Sufficient measurement surveys of field parameters must be made to provide adequate confidence that the magnitude and spatial distribution of variability are understood" (Wagner et al. 2006).

Lakes with irregular basins have larger 'development of shore line' factors (Hutchinson 1957), the ratio of the shoreline length relative to the circumference of a circle, than more circular/oval lakes. An irregular lake will have more perimeter to contribute nutrients via runoff, both natural and anthropogenic, than a round lake. In addition, the distribution of allochthonous nutrient inputs is often spatially heterogeneous due to variability in land use and subwatershed area, being higher in the vicinity of inlets and lake shores, than further away. Finally, irregular lakes are more hydrologically compartmentalized by geomorphology and bathymetry, making water quality more spatially heterogeneous than in round lakes (Van Nes & Scheffer 2005, Janssen et al. 2014). The lower internal connectivity (horizontal exchange) of irregular lakes restricts mixing and allows both physical and biogeochemical processes to establish and maintain heterogeneity in different lake compartments (Van Nes & Scheffer 2005). For these reasons, it is difficult to characterize irregular lakes according to standard indicators that assume homogeneity - overall lake trophic status is one example.

To understand the factors influencing nutrient biogeochemistry in irregular lake, it is useful to define spatially distinct regions that are relatively homogenous in characteristics and processes (e.g. embayments, beaches,open areas, etc). It is also important to be able to objectively group stations of similar water quality to remove bias. In the first part, we apply hierarchical cluster analysis to a 35-year, multivariable data set to characterize the spatial distribution of eutrophication indicators in a northern New England oligotrophic lake, specifically the Squam Lakes in New Hampshire (NH), USA. This approach objectively classifies sampling stations into regions with similar water quality for the period of record. Water quality at a specific site is the result of the interaction of a variety of driving forces, including freshwater inputs/outputs, sinks, and internal cycling. It is reasonable to assume that contiguous groups of stations with similar water quality are the result of comparable interactions, hence we call these regions zones of similar influence (ZSI, Boyer et al. 1997). The utility of this approach for further analysis and new hypothesis development are discussed.

The second part of this project concerns the determination of temporal trends in water quality indicators. One of the primary purposes for conducting long-term monitoring projects is to be able to detect trends in the measured variables over time. Most data sets generated during surveys and monitoring programs are interpreted using time series, where one of the axes is either time or distance. Due to the inherently complex character of natural phenomena, data are strongly affected by serial correlation and high variability can mask underlying patterns (trends, shifts, cycles, and seasonal variations). A battery of statistical techniques to study time series has been developed in the field of electrical signal analysis, economics, and quality control (Box et al. 1994; Chatfield 1996; Manson and Lind 1996; Emery and Thomson 2001). However, one difference in time series used in engineering and environmental sciences is that the latter rarely use data collected at regular intervals, either in time or space. Hence, it is normally necessary to perform a pre-treatment of the data sequence before attempting more orthodox statistical tests (Sturges 1983; Box et al. 1994; Chatfield 1996; Emery and Thomson 2001). To address these concerns we use Mann-Kendall test, LOESS, and spectral analysis to quantify and visualize trends.

Another problem is that climate-related time series usually contain combinations of variables measured at different time scales and locations. In the present study we attempt to link biogeochemical descriptors of water quality to external drivers, both natural and anthropogenic, using contrasting time series methods. Changes were investigated within the context of global and regional climatic stressors such as North Atlantic oscillation (NAO), Atlantic multidecadal oscillation (AMO), local rates of precipitation, and variations in freshwater runoff from the watershed.

Methods

Study Site

The Squam Lakes (Squam Lake and Little Squam Lake) are two conjoined lakes in central NH, USA connected by the Squam Channel, a short, natural channel (Fig. 1). The lakes sit at approximately 560 ft. (170 m) above mean sea level and their water levels are controlled by a dam on the Squam River, one mile downstream of the Little Squam Lake outflow (SLA 2002). The surface area of Squam Lake is 2,737.7 hectares with an average depth of 11 m and a maximum depth of 29.9 m. Squam Lake has an irregular shoreline, with 20 coves, 3 bays, 30 islands, and 13 open-water reefs (SLA 2002). The bathymetry of Squam Lake is irregular with many shallow sills which partition the lake into ~18 basins. Little Squam Lake, located downstream of Squam Lake, has a surface area of 165.1 hectares, an average depth of 7 m, and a maximum depth of 25.6 m. The Shoreline Development Index, $D_L = L/(2\sqrt{\pi A})$, for the combined Squam Lakes is 5.46, a large deviation from 1.0 of a circle lake. The Shoreline Density, $D_{SL} = L/A$, (Osgood 2005) is 35.9 m ha^{-1}; more than fivefold the shoreline of a circular lake of same area (D_{SL} = 6.58 m ha^{-1}).

The Squam Lakes watershed (Fig. 1) covers 171 km^2, 81% of which is forested. Land use in the watershed is rural, but with small-to-medium sized population centers. Development around the lake mostly consists of seasonal or year-round homes with on-site septic tanks. The western watershed area is much larger than that the eastern side and receives more stream drainage. Little Squam Lake has moderate-to-heavy development near its shoreline on all sides. The drainage basin to lake area ratio is low at 5.9 indicating potentially less impact of the watershed on water quality than lakes with higher ratios. The corollary is that the Squam Lakes have a relatively long hydraulic residence time of 227 days. A monitoring report (SLA 2002) estimated that 46% of water input to the Squam Lakes comes from tributaries distributed among 25 small sub-watersheds with 31% input from direct precipitation.

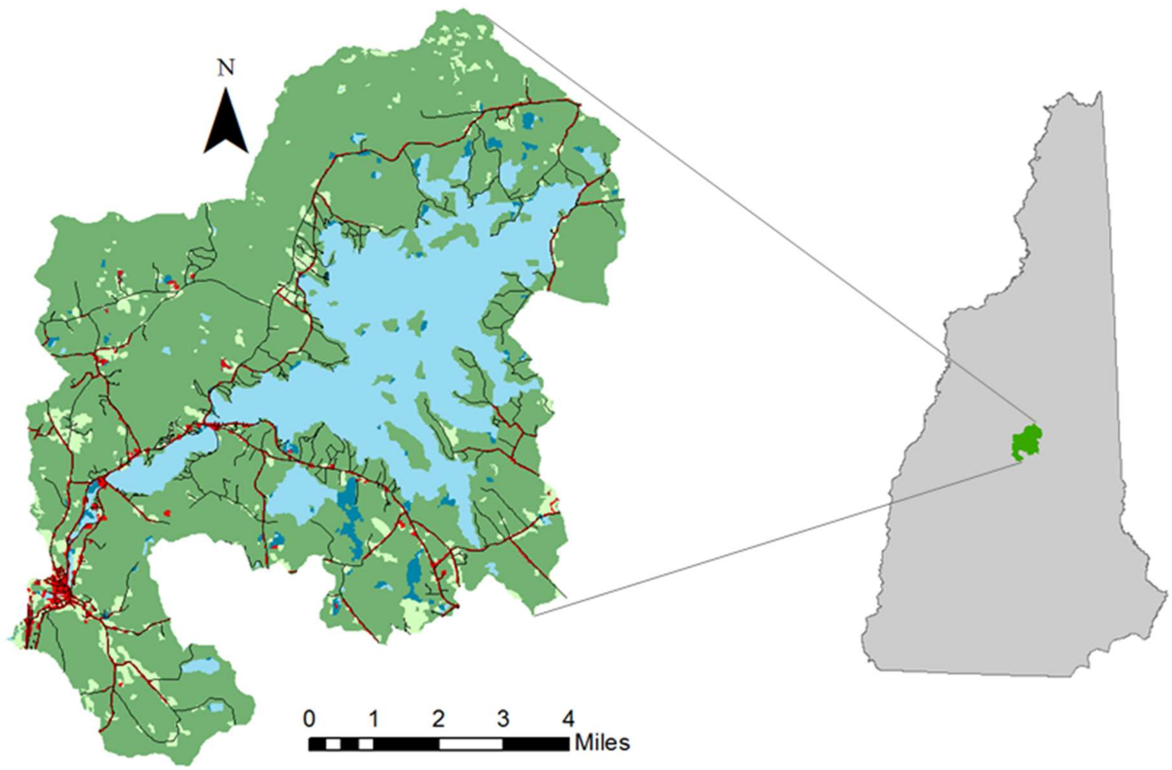

Figure 1. *Map of Squam Lakes watershed and lake area in New Hampshire USA (inset). Note the smaller sub-watershed area along the eastern side of the lake.*

Data Description

The data used in this study is the result of 385 water sampling events in the Squam Lakes collected from 1979 to 2014 by the Squam Lakes Association's network of volunteers in conjunction with by the University of New Hampshire Lay Lakes Monitoring Program and NH Department of Environmental Services. As frequently as bi-weekly (although often less frequently), integrated water samples were collected and analyzed using standard laboratory procedures for chlorophyll-*a* (Chl-*a*, µg L^{-1}), apparent color (COLOR, CFU), total phosphorus (TP, µg-P L^{-1}), and alkalinity (ALK, mg L^{-1}). Concurrent water clarity was measured in situ as Secchi depth (SD, m). Except for a few samples from 1990 through 1993, TP and ALK were not collected and analyzed until 1994, providing a shorter period of record than the other parameters.

Of the 22 stations monitored over the period of record, 16 possessed the longest and most complete records for analysis for at least one water quality parameter (Fig. 2). Of these, 3 stations had a 35 year record (1979-2014), 7 stations had records from 1979-2014 with some gap years, and 6 stations had records that started either after 1979 and/or ended before 2014. Of the variables measured, both Chl-*a* and SD had the longest and most complete records across stations. The monitoring stations were distributed across the lakes along shorelines, in coves, and in deeper parts of the lake. Three stations – Inner Squaw Cove, Outer Squaw Cove, and Inner Dog Cove – were shallow enough that SD measurements were occasionally limited by station depth.

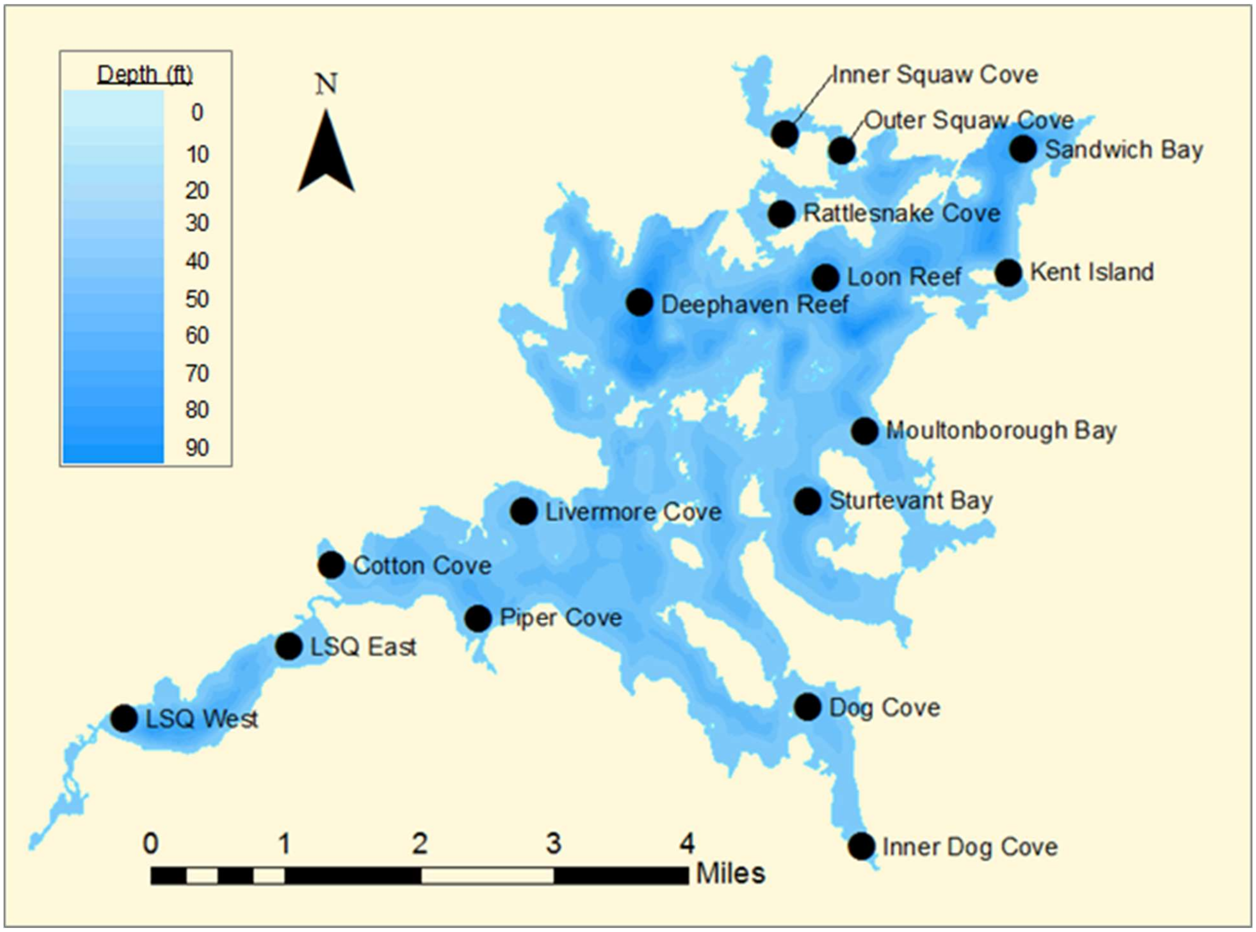

Figure 2. *Location and depth of sampling stations used in the analysis.*

The annual monitoring season typically begins in late May-early June and ends in late August-early September; less than 1% of water quality records were collected between October 1 and April 30. The semi-regular and seasonal pattern of water sampling result in a discontinuous time series that limited the types of statistical analyses available. Although intra-annual trends were not analyzed, other insights may be gained by examining the interannual trends in this record which spans 35 years.

Data Statistics

Typically, water quality data are skewed to the left (low concentrations and below detects) resulting in non-normal distributions, so it is more appropriate to use the median as the measure of central tendency because the mean is inflated by high outliers. In addition to numerical summaries, data distributions of water quality variables are reported as box-and-whiskers plots. The box-and-whisker plot is a powerful visual statistic as it shows the median, range, and distribution as well as serving as a graphical, nonparametric ANOVA. The center horizontal line of the box is the median of the data, the top and bottom of the box are the 25th and 75th percentiles (quartiles), and the ends of the whiskers are the 5th and 95th percentiles. The notch in the box is the 95% confidence interval of the median. When notches between boxes do not overlap, the medians may be considered significantly different. Outliers (<5th and >95th percentiles) were excluded from the graphs to reduce visual compression. Differences in variables were also tested between groups using the Mann-Whitney U test (comparable to a *t*-test) and among groups by the Kruskall-Wallace test (ANOVA) with significance set at $p<0.05$.

Spatial Patterns in Water Quality

It is useful to define sub-regions of ecosystems in order to understand the roles of various nutrient sources, sinks, and processes. Even a modest water quality monitoring program can generate a daunting amount of data (~30,000 points, this study). Because we were interested in understanding the spatial patterns of water quality in Squam Lakes, we wanted to reduce the data matrix into fewer elements. To identify any spatial similarities or differences among stations, water quality variables from 16 stations were clustered using the hierarchical Ward Linkage method (SPSS Statistics). The input variables used were Chl-*a*, SD, and COLOR. The actual data used in the cluster model were composed of statistical distribution characteristics for each variable – the range, median, median absolute deviation, interquartile range, and skewness. Although the TP data had shorter periods of record than other variables, we thought it too important to leave out, therefore, by including TP, we used a shorter but more robust dataset to develop spatial clusters. The results of this analysis were clusters of stations with similar water quality characteristics.

Time Series Analysis

Least squares, linear regression as a method for measuring change over time is useful for variables that change at a continuous rate. The simplicity of this method makes it appealing to those who are tracking water quality, but time series dominated by non-linear drivers may be skewed by endmember conditions. Therefore, we used the nonparametric Mann-Kendall Test (Minitab) on the annual median of variables for the time series. The Mann-Kendall Test is used to detect monotonic trends in environmental, climate, and hydrological data without the requirement that the measurements be normally distributed or that the trend be linear.

For external drivers such as precipitation which respond in a cyclical manner, the slope of a best-fit line may be skewed in either direction depending on whether the time series starts and/or ends in a trough or a crest on the sinusoidal curve. For cycles with longer frequencies relative to the period of record, the best-fit line is more sensitive to this effect. To uncover a long-term trend in a time series, any cyclical components of the time series should be identified. There may be multiple cycles of varying frequencies in the water quality datasets.

Cross-spectral analysis has been applied in other scientific fields to investigate simultaneously the relationship and corresponding time lags between two stationary time series in the frequency domain. In the Squam Lakes station time series, some dominant cycles may be apparent by eye. These cycles may be identified through spectral analysis – computing the sinusoids which best fit a time series.

Spectral analysis was performed to identify interannual cycles in each water quality parameter at each station and for each group of stations, grouped using the forementioned spatial clustering. Examining the similarities and differences in cycles at the station-level might identify individual stations whose water quality is responding to different driving factors. Examining these similarities and differences at the cluster-level might help identify the influential drivers for regional and even lake-wide water quality.

Least-squares spectral analysis (LSSA) is the process of fitting sinusoids to time series data to create the best fit based on least squares. While some spectral analysis methods require a continuous or regularly-sampled dataset, LSSA is useful for discontinuous time series with irregular gaps. To weight each year and each station equally, LSSA was performed on time series of the annual median values for each water quality parameter rather than on time series of every sampling event. Some years and stations would otherwise be given more weight because there were irregularities in sampling frequency and length of sampling seasons between monitoring stations and between years within a stations' datasets. Furthermore, fitting sinusoids to time series that include every sampling event would identify higher-frequency intra-annual trends that would distract from the interannual trends this study seeks to examine.

The dataset was sorted by water quality parameter and then by station and by group of stations for the spectral analysis. The annual median values of each water quality parameter at each station and group of stations was calculated and prepared for spectral analysis as time series with one data point per year. No interpolation or gap-filling was performed, as would be done for spectral analyses that required a continuous or regular time series. Any gaps in the time series were gaps of one or more years, rather than gaps of irregular frequency and length.

Relationship to Drivers

As proxies for runoff, precipitation and streamflow time series in the region were analyzed to examine cyclical patterns that may drive water quality in the Squam Lakes. The nearest complete precipitation dataset, 1979-2014, was from the Concord Municipal airport, 37 miles from the center of Squam Lake. The nearest river gauges with complete streamflow records for this time period were on the Pemigewasset River in Plymouth, NH, on the Smith River in Bristol, NH, and on the Winnipesaukee River in Tilton, NH – 8, 16, and 21 miles from the center of Squam Lake, respectively. The Pemigewasset-Plymouth gauge has a drainage area of 1,611 km^2, the Winnipesaukee-Tilton gauge has a drainage area of 1,220 km^2, and the Smith River has a drainage area of 223 km^2. Only the 1979-2014 data for these precipitation and streamflow time series were used in the spectral analysis to avoid identifying any interannual cycles that occurred prior to 1979 but did not persist after 1979.

Results

Overall Water Quality of Squam Lakes

Summary statistics for all water quality variables from for "summer" sampling events (June-Sep.) for the Squam Lakes exhibited very good water quality (Fig. 3) with median SD of 7.1 m, Chl-*a* of 1.9 ppb, COLOR of 9.4 CPU, TP of 6.5 ppb, and ALK of 6.2 ppm. Difference between lakes were significant but very minor. Little Squam had higher SD (p=0.0119) but lower COLOR (p=0.0007), TP (p=0.0001), and ALK (p=0.0001) than Squam. There was no significant difference in Chl-*a* between lakes. From this data, the Squam Lakes are considered oligotrophic water bodies.

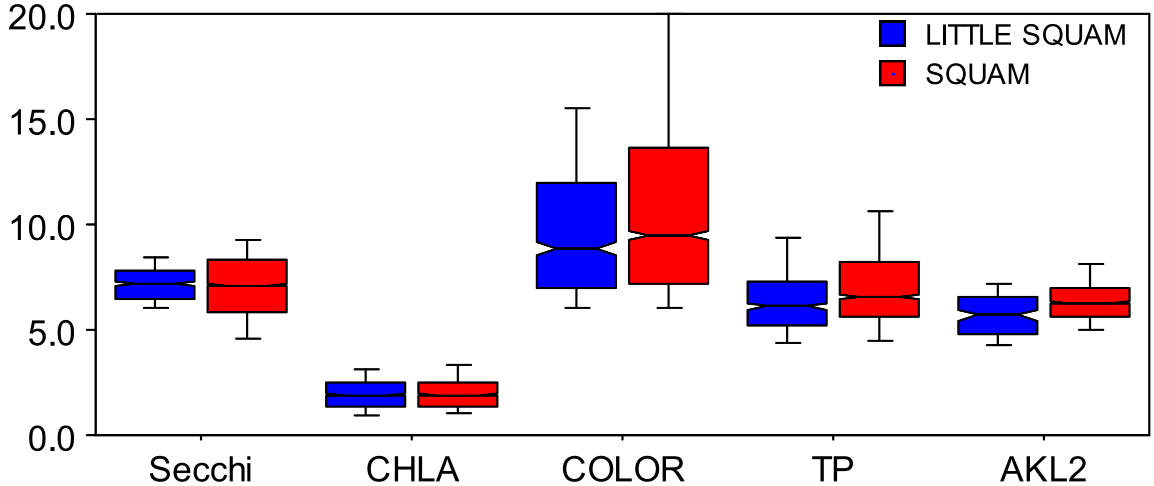

Figure 3. *Box and whisker plot of SD (m), Chl-a (ppb), COLOR (CPU), TP (ppb), and ALK (ppm) by lake.*

Spatial Trends

The clustering approach produced an array of rescaled distance values between each of the monitoring stations. Plotting these values using a dendrogram (Fig. 4) illustrates which stations are most similar to each other. Clustering the monitoring stations based their statistical "distance" is rather subjective. Delineating groups requires decisions about how many groups there should be and what statistical distance is "significant." We chose to group stations into 5 clusters based on natural breaks in the dendrogram. The monitoring stations may also be combined into clusters using a Ward's distance of 5, which creates 7 groups. In this clustering scheme, Inner Squaw Cove would separate from Outer Squaw Cove, and Cotton Cove and Sturtevant Bay would separate from Dog Cove and the Little Squam stations. Using a Ward's distance of 13 would consolidate 13 stations; the Western, Northeastern, and Little Squam & Southern stations, which we felt was too agglomerative, the 5 cluster grouping seemed to provide the best balance.

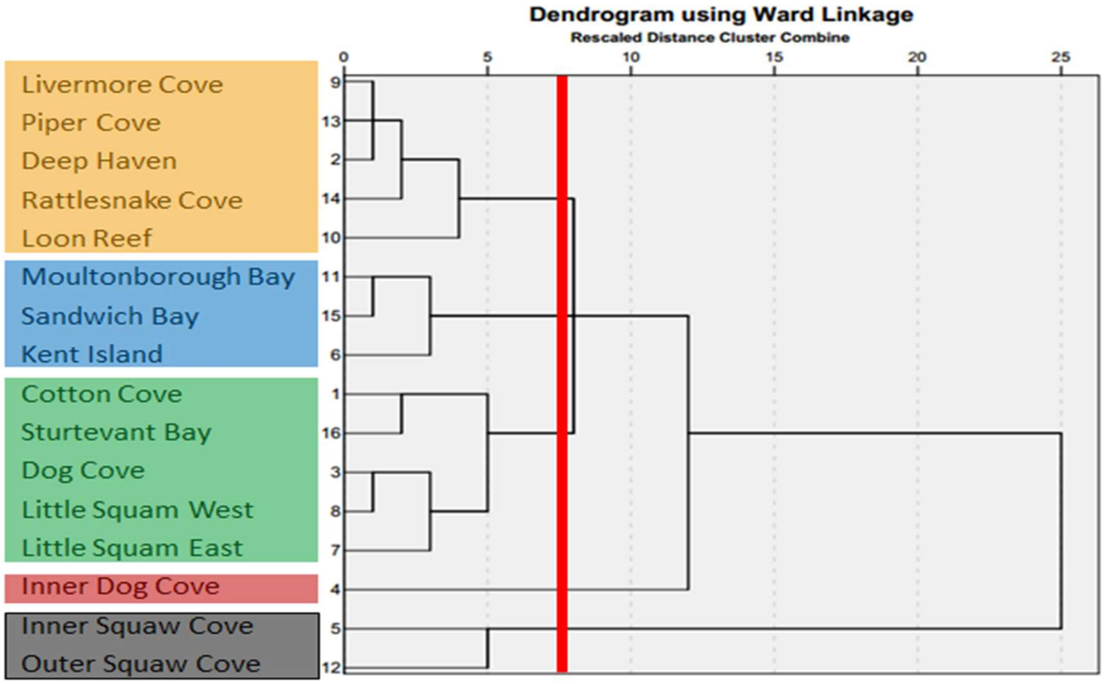

Figure 4. *Results of hierarchical cluster analysis showing station grouping as function of similarity in water quality.*

Plotting these cluster associations on a map of monitoring stations shows similarities in water quality across the lakescape (Fig. 5).

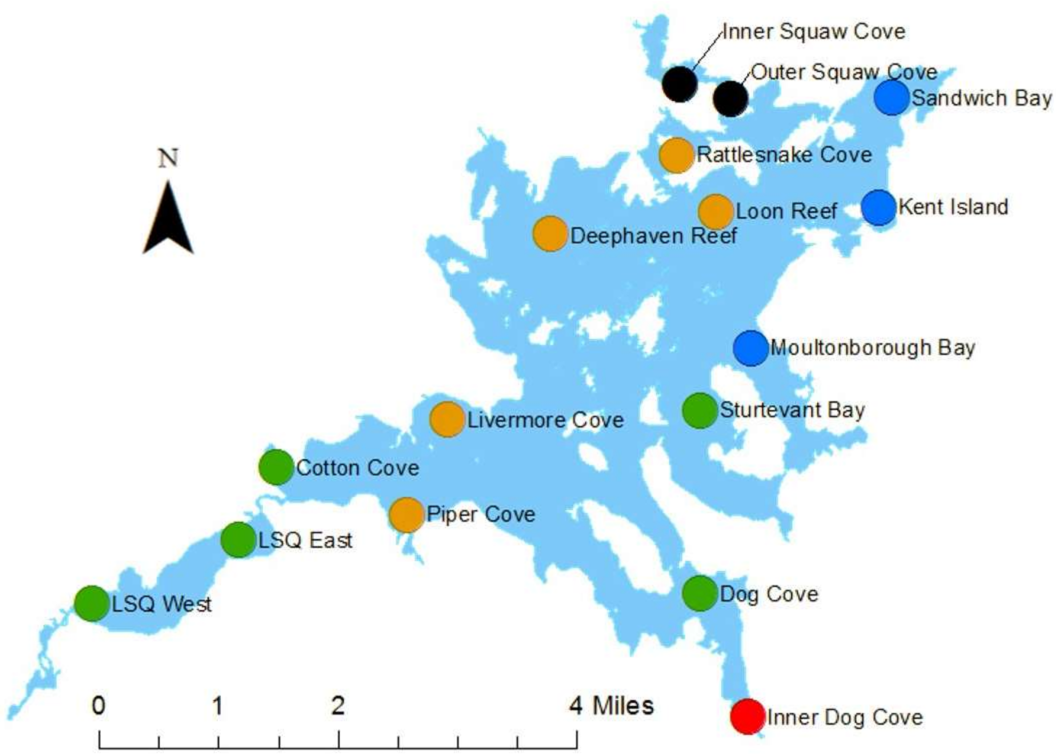

Figure 5. Sampling stations color coded with previous cluster affiliations.

In an effort to understand which water quality variables were most responsible for cluster grouping, we plotted box-and-whisker plots of SD, TP, Chl-*a*, and Color by cluster (Fig. 6). SD was an important driver in cluster affiliation as almost all clusters were significantly different for that variable.

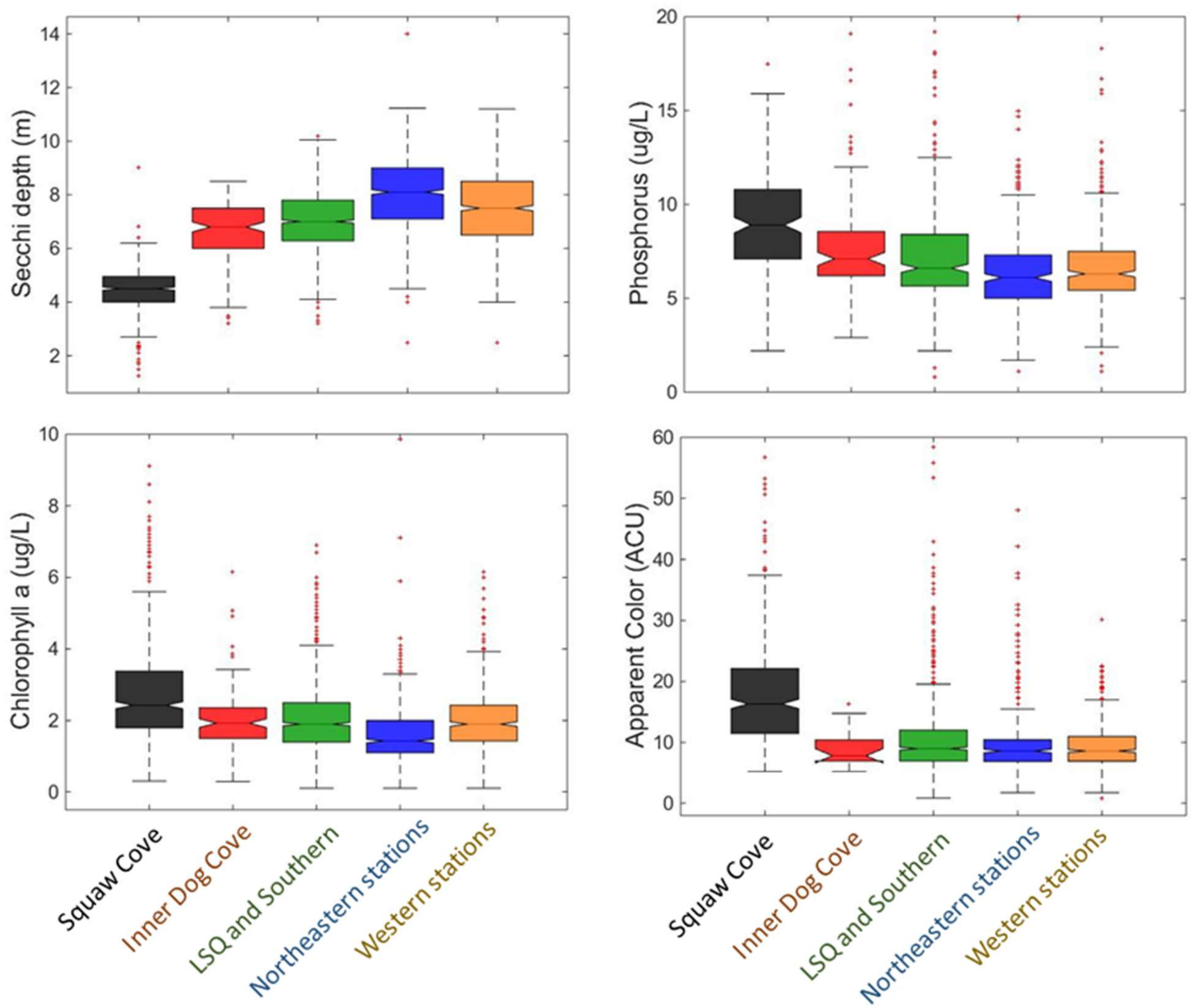

Figure 6. *Box-and-whisker plots of water quality variables as function of cluster showing the relationships among variables and importance in cluster determination.*

The clusters also allowed us to compare variables not included in the model such as ALK which was significantly higher in Squaw Cove group than all the others (not shown). The comparison of station cluster water quality was combined in a matrix showing the relative differences across the lakes (Table 1). The Squaw Cove sites had poorest water quality due to low water clarity and high TP and Chl-*a*. This area also has high Color as a result of it draining a large wetland area. In contrast, stations in northeast region had the best water quality.

Squam Lakes Station Cluster Characteristics						
Cluster	**Stations**	**Secchi**	**Chl-*a***	**TP**	**Color**	**Alkalinity**
1	Inner/Outer Squaw Cove	LOW	HIGHEST	HIGHEST	HIGHEST	HIGHEST
2	Inner Dog Cove	LOWEST	MED	MED	LOWEST	HIGH
3	LSQ, Southern Stations	MED	MED	MED	MED	MED
4	Northeastern Stations	HIGH	LOWEST	LOWEST	MED	MED
5	Western Stations	HIGHEST	MED	MED	MED	LOWEST

Table 1. *Matrix of water quality across clusters color coded with red as poorest quality and green as best.*

Temporal Trends

Chl-*a* concentrations have decreased at some monitoring stations while increasing at others (Table 2). Due to this spatial variability, Chl-*a* concentrations cannot be said to have significantly increased or decreased lakewide in Squam Lake. Chl-*a* has increased significantly at the two monitoring stations located in Little Squam Lake; increasing at rates of .024 and .057 $\mu g\ L^{-1}\ yr^{-1}$ over the length of their records. Of the three monitoring stations in the southern part of Squam Lake - Cotton Cove, Sturtevant Bay, and Dog Cove - which were grouped with the Little Squam Lake monitoring stations in the cluster analysis, Chl-*a* is increasing at one, decreasing at another, and remaining steady at the other.

Station	Chlorophyll *a*				Secchi depth				Total phosphorus			
	y-intercept	Slope	R	p	y-intercept	Slope	R	p	y-intercept	Slope	R	p
Livermore Cove	1.6	0.015	0.17	0.00	7.5	-0.016	-0.15	0.00	5.6	0.086	0.19	0.04
Piper Cove	2.3	-0.011	-0.10	0.19	6.8	-0.002	-0.01	0.83	7.6	-0.049	-0.07	0.44
Deep Haven	2.3	-0.020	-0.13	0.37	7.8	0.058	0.30	0.06	7.2	-0.083	-0.17	0.25
Rattlesnake Cove	1.9	0.003	0.05	0.70	6.1	0.032	0.57	0.00	6.7	-0.005	-0.01	0.93
Loon Reef	2.2	-0.020	-0.14	0.31	9.0	-0.004	-0.02	0.74	7.5	-0.070	-0.15	0.26
Moultonborough Bay	1.9	-0.007	-0.06	0.40	7.3	-0.005	-0.03	0.56	7.9	-0.077	-0.14	0.14
Sandwich Cove	2.1	-0.015	-0.12	0.05	7.4	0.027	0.18	0.00	7.4	-0.074	-0.11	0.25
Kent Island	1.5	-0.003	-0.03	0.67	8.6	0.007	0.07	0.14	6.0	0.078	0.08	0.50
Cotton Cove	1.4	0.036	0.33	0.00	6.8	-0.025	-0.24	0.00	9.8	-0.100	-0.08	0.37
Sturtevant Bay	2.1	-0.014	-0.14	0.02	7.5	0.009	0.08	0.09	-0.9	0.886	0.19	0.06
Dog Cove	2.0	0.000	0.00	0.97	6.3	0.003	0.03	0.72				
Little Squam West	1.6	0.024	0.23	0.00	7.4	-0.007	-0.07	0.14	7.1	-0.041	-0.07	0.42
Little Squam East	1.5	0.057	0.37	0.00	7.3	-0.015	-0.11	0.07				
Inner Dog Cove	2.5	-0.035	-0.16	0.07	7.0	-0.031	-0.10	0.23	7.1	0.064	0.09	0.32
Inner Squaw	3.5	-0.022	-0.11	0.04	4.2	0.002	0.02	0.76	11.5	-0.080	-0.05	0.62
Outer Squaw	3.2	-0.040	-0.24	0.00	4.5	0.007	0.10	0.10	11.5	-0.218	-0.09	0.43

Table 2. *Linear trends of water quality parameters Chl-a, SD, and TP at each monitoring station.*

Similarly, SD trends across the lakes show no consistent lakewide increase or decrease. Within groups of monitoring stations, SD increases at some stations while decreasing at others. For TP, the trend towards higher concentrations at two monitoring stations was marginally significant. No monitoring stations exhibited a significant decrease in TP concentrations.

Spectral Analysis

Spectral analysis can be a useful statistical tool for identifying variables that drive water quality change. Spectral analysis performed on a time series of any suspected driving factor can reveal the dominant time periods on which it operates. Time series with similar apices in spectral power can indicate that two variables are related.

There are a number of variables that could drive water quality in a lake, but a few for which time series are readily obtainable and that operate in a cyclical manner. Of these, precipitation and streamflow – proxies for runoff – potentially have a direct impact on water quality. Temperature and atmospheric oscillations have cyclical patterns and may affect water quality, although less directly than runoff. Land use in a lake's watershed could have a direct impact on water quality, but land use patterns are difficult to quantify and are unlikely to be cyclical in nature.

The output of the spectral analysis is a power density spectrum which can be plotted on a periodogram (Fig. 7). The frequencies, in years, with the greatest power spectral density are the frequencies at which the strongest cycles occur. In any periodogram, these apices in power spectral density could indicate that there is a strong cycle in the data occurring at that frequency, or that the apex occurred at that frequency by chance.

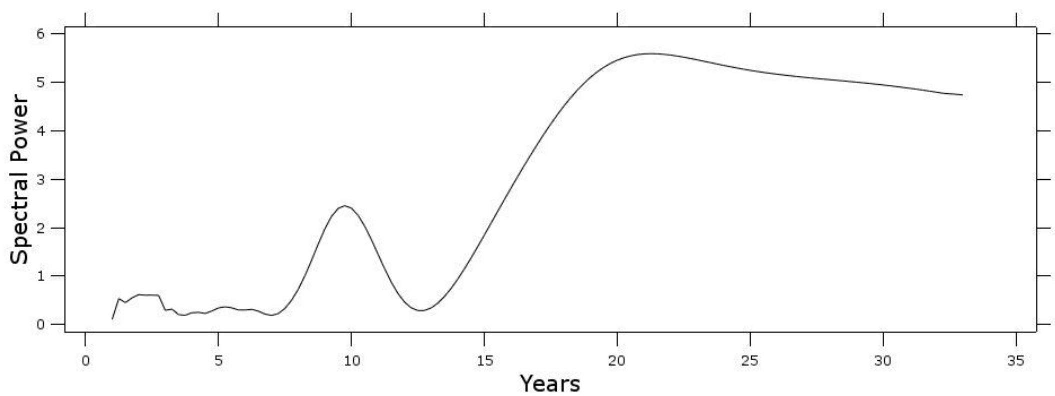

Figure 7. *Example of periodogram from spectral analysis on median annual Chl-a records from Livermore Cove.*

Strong apices that occurred in multiple periodograms were inspected to ensure they were not products of the length of record. An apex around 17 years - approximately half the length of record - was present in several periodograms, but not many, and is not suspected to be a product of the length of record.

Periodograms of related environmental processes are expected to have similarities. At the three river gages nearest to the Squam Lakes, the periodograms show a dominant cycle of approximately 25-30 years and a less dominant cycle of approximately 18 years (Fig. 8). Discharge is expected to correlate with runoff and thus be related to the water quality of lakes. Comparing the periodograms of discharge with those of water quality can indicate whether these environmental processes vary on similar time scales.

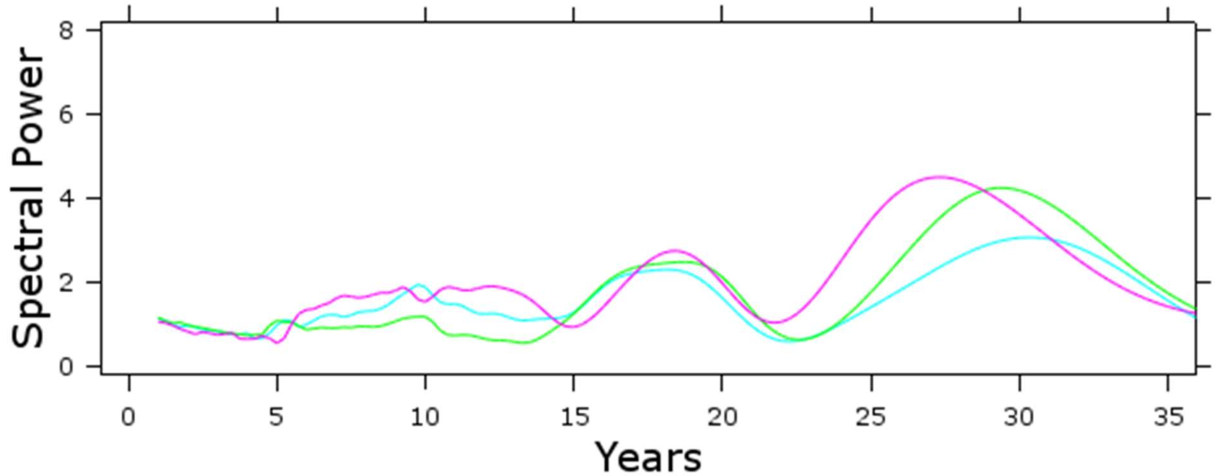

Figure 8. *Periodograms of river discharge at three nearby river gages: Smith River (cyan), Pemigewasset River (green), and Winnipesaukee River (magenta).*

For SD at the five groups of water quality monitoring stations in the Squam Lakes, there are noticeable apices in the periodogram between 5 and 10 years (Fig. 9). These apices share a similar characteristic for the four groups of stations with the longest records - they have an apex around 5-6 years, although this apex is small at the Little Squam Lake and Southern Squam stations, and they have an apex around 9-10 years, although this apex is small for the Northeastern stations. The Little Squam Lake and Southern Squam groups have dominant apices around 18-20 years, similar to the apices observed around 15-20 years at the three nearby river gages.

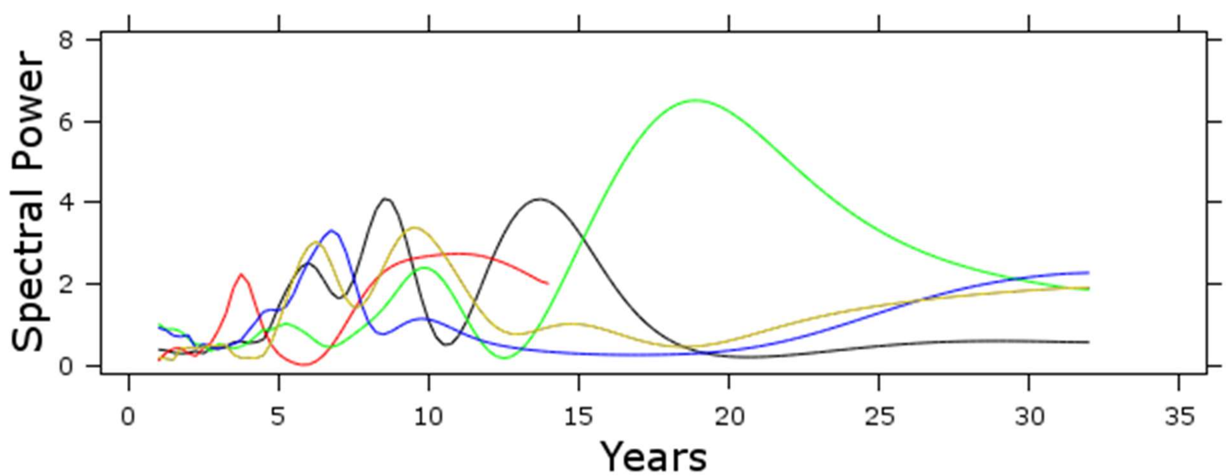

Figure 9. *Periodograms of annual secchi depth at five groups of monitoring stations in the Squam Lakes: Squaw Cove (black), Inner Dog Cove (red), Little Squam & Southern (green), Northeastern (blue), and Western monitoring stations (yellow).*

There is little similarity among the periodograms for Chl-*a* concentrations (Fig. 10). One noteworthy feature in these periodograms is the dominant apex around 15-20 years for the Northeastern group of stations - a cycle similar to that observed in the three nearby river gages. Other noteworthy features of these periodograms are the elevated spectral power near the low-frequency end of the periodogram. This indicates variability on a time scale close to, or longer than, the period of record. However, there is no consistent long-term, linear trend in Chl-*a* concentrations lake-wide. The lack of a consistently dominant cycle in Chl-*a* among the groups of stations suggests that spatial correlation in Chl-*a* may be weak.

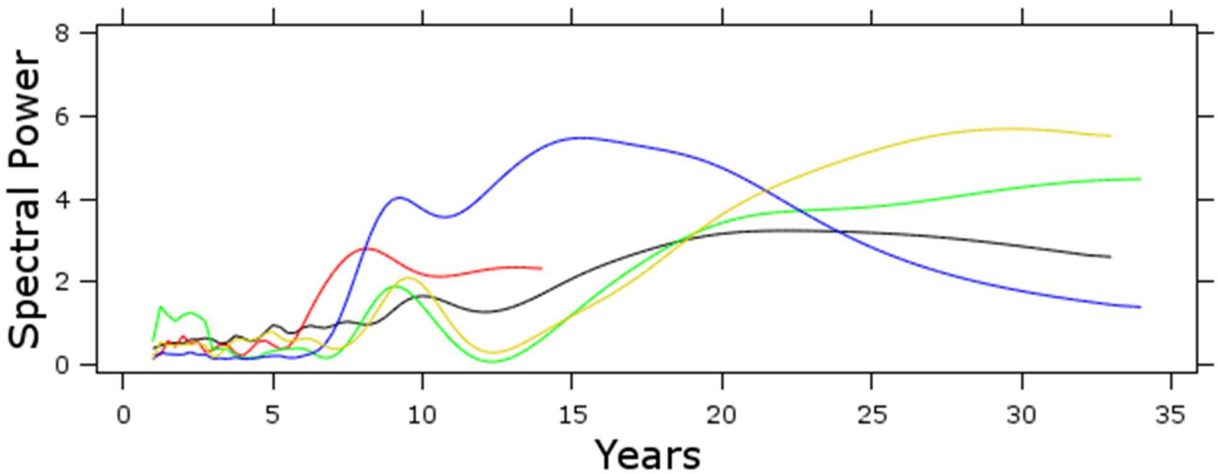

Figure 10. *Periodograms of annual Chl-a concentrations at five groups of monitoring stations in the Squam Lakes: Squaw Cove (black), Inner Dog Cove (red), Little Squam & Southern (green), Northeastern (blue), and Western monitoring stations (yellow).*

The relatively short period of record for TP concentrations in the Squam Lakes limits the usefulness of spectral analysis. There is a lack of a consistent, dominant cycle among the groups, but the relative spectral power on the low-frequency versus high-frequency ends of the periodogram can be meaningful (Fig. 11). The Western group and Squaw Cove group of stations has more low-frequency than high-frequency variability, indicating that drivers of TP concentration operate on scales greater than the length of this record.

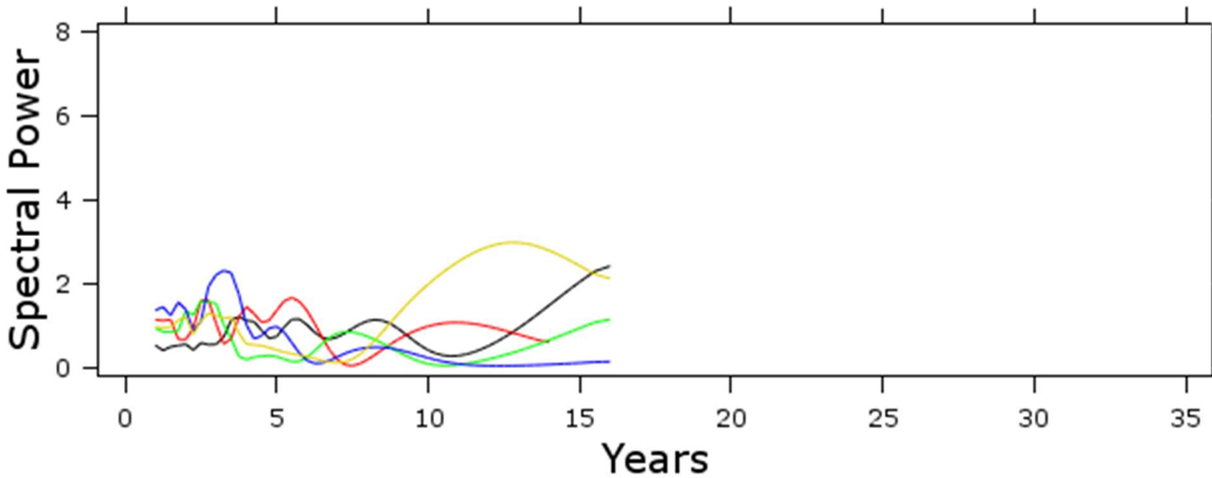

Figure 11. *Periodograms of annual TP concentrations at five groups of monitoring stations in the Squam Lakes: Squaw Cove (black), Inner Dog Cove (red), Little Squam & Southern (green), Northeastern (blue), and Western monitoring stations (yellow)*

Spectral analysis of water quality at the Squam Lakes groups of stations shows little spatial correlation relative to the river discharge datasets. Although there were consistent cycles apparent in the river discharge periodograms, there appears to be no cyclical force that drives water quality interannually. The spectral analysis performed on the Squam Lakes water quality dataset suggests that variability in water quality is concentrated more on the high-frequency end of the periodogram than on the low-frequency end, except for a portion of water quality records for some groups of stations. This suggests that long-term trends detected in many time series in the Squam Lakes dataset should be treated cautiously - a detected trend could be heavily influenced by whether the time series began and ended in a period of particularly high or low nutrient concentrations or water clarity.

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