remote sensing

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Spatiotemporal Variability of Lake Water Quality in the Context of Remote Sensing Models

Carly Hyatt Hansen [1,*], Steven J. Burian [1], Philip E. Dennison [2] and Gustavious P. Williams [3]

1 Department of Civil and Environmental Engineering, University of Utah, Salt Lake City, UT 84112, USA; steve.burian@utah.edu
2 Department of Geography, University of Utah, Salt Lake City, UT 84112, USA; dennison@geog.utah.edu
3 Department of Civil and Environmental Engineering, Brigham Young University, Provo, UT 84602, USA; gus.p.williams@byu.edu
* Correspondence: carly.hansen@utah.edu

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Abstract: This study demonstrates a number of methods for using field sampling and observed lake characteristics and patterns to improve techniques for development of algae remote sensing models and applications. As satellite and airborne sensors improve and their data are more readily available, applications of models to estimate water quality via remote sensing are becoming more practical for local water quality monitoring, particularly of surface algal conditions. Despite the increasing number of applications, there are significant concerns associated with remote sensing model development and application, several of which are addressed in this study. These concerns include: (1) selecting sensors which are suitable for the spatial and temporal variability in the water body; (2) determining appropriate uses of near-coincident data in empirical model calibration; and (3) recognizing potential limitations of remote sensing measurements which are biased toward surface and near-surface conditions. We address these issues in three lakes in the Great Salt Lake surface water system (namely the Great Salt Lake, Farmington Bay, and Utah Lake) through sampling at scales that are representative of commonly used sensors, repeated sampling, and sampling at both near-surface depths and throughout the water column. The variability across distances representative of the spatial resolutions of Landsat, SENTINEL-2 and MODIS sensors suggests that these sensors are appropriate for this lake system. We also use observed temporal variability in the system to evaluate sensors. These relationships proved to be complex, and observed temporal variability indicates the revisit time of Landsat may be problematic for detecting short events in some lakes, while it may be sufficient for other areas of the system with lower short-term variability. Temporal variability patterns in these lakes are also used to assess near-coincident data in empirical model development. Finally, relationships between the surface and water column conditions illustrate potential issues with near-surface remote sensing, particularly when there are events that cause mixing in the water column.

Keywords: spatiotemporal variability; water quality; chlorophyll-a; near-coincident remote sensing

1. Introduction

Over the past decade, remote sensing of water quality has become more widely used and the extent of applications has grown tremendously, especially in non-coastal environments. Notable inland water quality applications of remote sensing include large-scale quality and clarity surveys [1–4] and real-time tracking and forecasting of nuisance algal blooms (NABs) or harmful algal blooms (HABs) [5,6]. The general process of developing an empirical remote sensing model for algal blooms typically involves: downloading and processing of remote sensing imagery (which may include atmospheric correction and conversion from digital numbers to reflectance at the near-surface of the water body), collecting coincident (or near-coincident) field measurements of chlorophyll-a (or other parameters related to biomass or levels of toxins), and using regression or other statistical modeling techniques to develop a relationship between the field-measured concentrations and remotely sensed reflectance from the corresponding pixel or group of pixels. Multiple sensors offer greater coverage with varying overpass frequencies and extents, and band combinations which are more optimal for characterization of water quality conditions. Increased availability of imagery data and processed data products has also facilitated increased use and application. Despite all of these advances, there are a number of issues that remain to be addressed to support more effective and accurate remote sensing model development and application. Many of these issues stem from traditional assumptions associated with the use and application of remote sensing data, and do not consider conditions and processes that are specific to the water bodies of interest.

Water quality conditions, particularly algal growth, in lakes and reservoirs have been shown to change relatively quickly (i.e., seasonally or sub-seasonally) [7–9]. Algal bloom variability in inland waters also occurs on smaller spatial scales than in the open ocean. Spatial and temporal variability in water quality may be caused by a number of processes, such as resuspension of suspended sediments and point-source inflow of nutrients [10]. Increased variability in lake and reservoir water quality requires that in situ data used to develop remote sensing water quality models represent conditions at the time of the imagery acquisition–to the extent possible. Often, the historical records do not provide exact temporal matches between the in situ samples and the satellite overpass, requiring the use of "near-coincident" data, or some relaxation of a definition of a "match." Coastal and lake water clarity and quality remote sensing literature report a wide range of time-windows for considering data to be near-coincident. Reported windows range from ± 3 h [11], same day [12], one day [4,13], seven days [2,14], to ± 10 days [1] between the satellite image acquisition and the field samples used for calibration. Often, a particular time-window for near-coincident matches is arbitrarily chosen (e.g., using an arbitrary increase in the percentage of samples that match with a satellite image [15]), or the study states that the relaxation of the time-window improved the model fit, without detailing the actual improvement [1].

Another issue that is often overlooked in water quality remote sensing applications is thorough review and evaluation of appropriate sensors in the context of a specific water body (which has unique spatial and temporal characteristics). Sensor characteristics can have large implications for the utility of the resulting model and dataset. Model application determines the sensor choice and could depend on a number of factors: the spatial resolution (which is limited by the size of the water body or multiple waterbodies in a region), the spatial variability within the water body, the desired return time (which is influenced by the temporal variability of the water quality processes), the length of historic record, spectral resolution (which determines the ability of the sensor to discriminate or more accurately determine conditions and which parameters can be estimated), the available processing resources (from the imagery data and data products to the personnel who will perform data processing and analysis), and the scope of the application (both spatial and temporal). For empirical model development, information from the field (e.g., concentration of chlorophyll-a measured at a single point on the water body) is matched to information from the satellite (reflectance averaged over a single pixel or group of pixels). Therefore, the spatial variability of the water body may influence the choice of satellite. For example, if the algae concentrations vary substantially on the order of 20–40 m, then a satellite with a resolution of 30 m will be sufficient, while a satellite with a resolution of 500 or 1000 m would be too coarse to adequately represent the variability of the chlorophyll concentrations. One review suggests different medium spatial resolution satellites (e.g., Landsat) and coarser spatial resolution satellites (e.g., MODIS) for water clarity and quality studies be selected based primarily on the size of the water body [16], however, other characteristics of the lake, namely the ability of different spatial resolutions (e.g., Landsat resolution of 30 m or SENTINEL-2 resolution of 10–60 m compared to MODIS resolution of 250–1000 m) to represent spatial variability within the lake or the ability of more frequent overpasses to address temporal variability (e.g., Landsat every 16 days compared to SENTINEL-2 every 5 days and MODIS every 1–2 days) are not considered.

Finally, remotely sensed data are limited by the optical depth of the water column (the depth at which light is able to penetrate), which means that the estimates are limited to near-surface algae populations. Optical depth is also a function of chlorophyll concentration; as the near-surface algae populations increase, optical depth decreases. However, algae thrive not only at the surface but exist throughout the water column. Algal population characteristics (species, diversity, etc.) may vary with depth, especially when the water column is stratified and there are differences in oxygen or salinity [17,18]. Concerns have been raised about the utility of only sensing and estimating the surface of the lake given these variable conditions throughout the water column. It is therefore important to explore the relationship between surface and water-column algae concentrations and the variability within the water column when evaluating the limitations of remotely-sensed surface estimates.

This study uses field measurements of chlorophyll to evaluate techniques and assumptions that are often used in remote sensing models of algae and surface water quality. While there are many additional considerations for water quality (particularly algae/chlorophyll concentrations) this paper focuses on the three issues outlined above: (1) selecting sensors which are suitable for the spatial and temporal variability in the water body; (2) determining appropriate uses of near-coincident data in empirical model calibration; and (3) recognizing potential limitations of remote sensing measurements which are biased toward surface and near-surface conditions.

Study Area

The study area for this paper is the Utah Lake and Great Salt Lake (GSL) system. This lake system is important for recreation and ecosystem services for the urban areas that are concentrated in the hillsides and valleys to the east of these lakes. During the summer of 2016, Utah Lake and Farmington Bay of the GSL experienced massive cyanobacterial algal blooms. While large algal blooms in these lakes are not particularly rare, the rapid development and magnitude of the recent blooms spurred widespread attention and motivated increased interest in monitoring these waters, particularly through remote sensing because the size of the lakes make them difficult to monitor through field sampling alone. Data were collected with water quality sondes at a number of locations throughout the system (shown on the map in Figure 1) throughout the summer of 2016 to support this research.

Previous studies in the Utah Lake and GSL system have explored variation in algal speciation throughout the growing season and environmental factors which contribute to species diversity [19–22]. Historical sampling campaigns on Utah Lake revealed typical algal succession, with diatoms and then green algae dominating in early summer, and then cyanobacteria dominating during the late summer months, and a general decrease in species diversity throughout the summer [21,22]. In Farmington Bay and the GSL, studies have focused on speciation and presence of toxins in cyanobacteria. These studies have found seasonal trends in algae growth and have observed stark differences between algae types in different regions of the GSL and Farmington Bay [19,20,23,24]. These studies improve understanding of the algae populations in this lake system; however, they lack important information about spatial or temporal variability at scales that are necessary for improving remote sensing model development.

The Great Salt Lake is divided roughly in half by a railroad causeway which runs East-West, separating the much more saline (roughly 28% salinity) North Arm, which includes Gunnison Bay and Bear River/Willard Bay, from the South Arm (Gilbert Bay and Bridger Bay) and Farmington Bay, which is further separated by an automobile causeway. These bays maintain a salinity between 11% and 15% [25] and at the north end of Farmington Bay, salinity is typically around 8% [20]. These lakes are relatively shallow, with an average depth of approximately 4.2 m in Gilbert Bay and an average depth of approximately 1 m in Farmington Bay. Secchi depth (as a measure of transparency) ranges between 2 and 5 m in the South Arm of the GSL, while in Farmington Bay, it is regularly less than 0.3 m [26]. Utah Lake, which flows into the Great Salt Lake through the Jordan River is also a shallow lake (average depth of 2.74 m) and while it is a freshwater lake, it has high dissolved solids, resulting in slightly saline conditions [27]. High rates of suspended sediments result in high turbidity, and prior to the large algal bloom in 2016, the Secchi depth in the middle of Utah Lake was roughly 0.2 m.

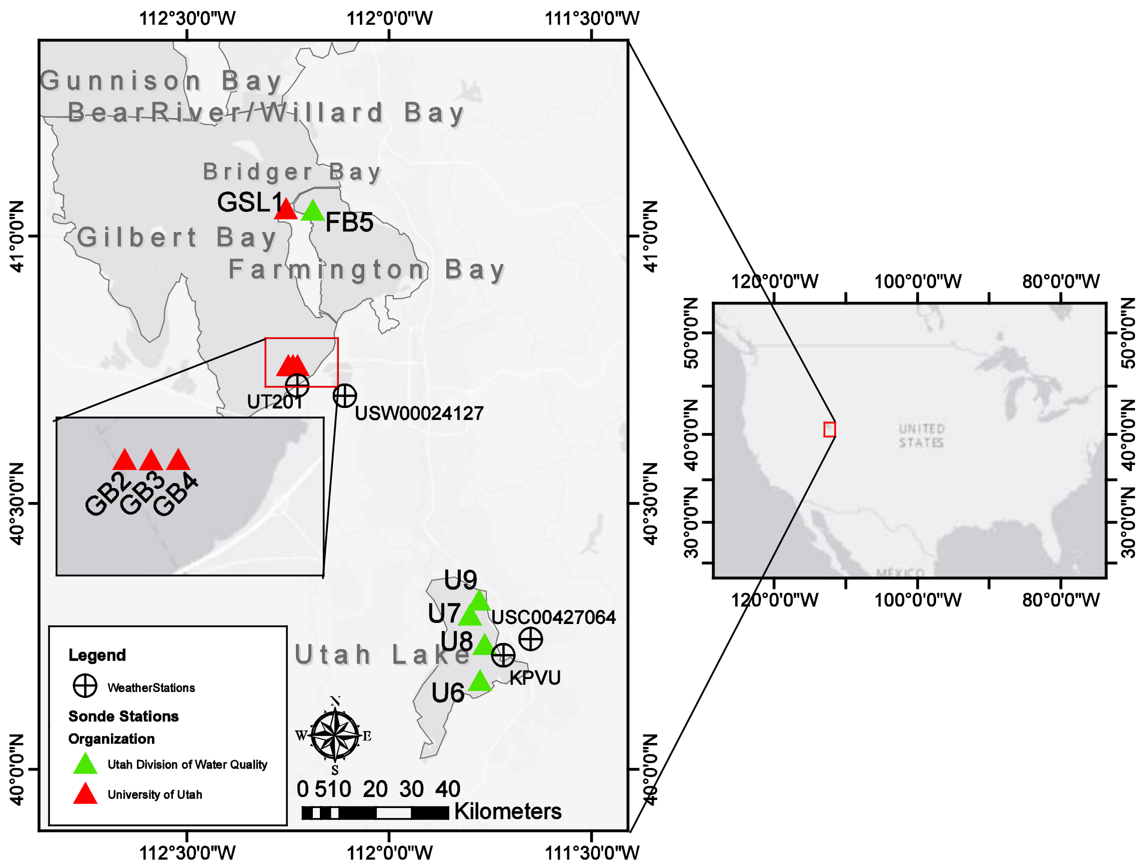

Figure 1. Sampling Locations and Study Area.

2. Materials and Methods

2.1. Data Collection

The collection of water quality samples was designed to provide information about algae biomass (measured as chlorophyll-a) and its: (1) temporal variability (through repeated sampling visits and high-frequency sampling); (2) spatial variability (through multiple sites and/or offsets); and (3) surface–water column relationships. Chlorophyll-a data were collected by researchers at the University of Utah (U of Utah) using a Hydrolab DS5 (OTT Hydromet) multiparameter sonde equipped with a submersible fluorescence Chlorophyll-a sensor (range of 0.03–500 µg/L). Chlorophyll-a data were also provided by the Utah Division of Water Quality (UDWQ) measured using YSI EXO 2 multiparameter sonde (with submersible fluorescence Chlorophyll-a sensor (range of 0–400 µg/L) coupled with a Nexsens CB-450 buoy platform. Sampling locations were chosen based on accessibility. During the study period, low water levels, exposed reef-like bioherms, and deep sediments restricted boat and individual access to many locations in the lakes that may otherwise have been sampled. Details of the sampling at each station are summarized below and in Table 1, including the duration of sampling periods and the types of samples collected. Durations and frequencies of data collection were determined by the availability of equipment and personnel, and local weather conditions. Data collected by the University of Utah are shared under the Creative Commons Attribution CC BYU License [28] and data collected by the UDWQ are available through the iUTAH Time Series Analyst data portal.

Table 1. Summary of Data Collection Periods and Methods.

Lake	Stations	Organization	Sampling Periods (2016)	7.5 m Offsets	Surface (<1 m)	Water Profiles	Approximate Lake Depth During Study Period (m)
Main GSL	GSL1	U of Utah	23–31 July	X	X	-	0.8
	GB2; GB3; GB4	U of Utah	6–16 June; 6–14 July; 12–22 Aug	X	X	X	5.1
Farmington Bay	FB5	UDWQ	8 July–28 July	-	X	-	0.5
Utah Lake	U6; U7; U8	UDWQ	28 Aug–13 Sept	-	X	-	1–1.5
	U9	UDWQ	15 July–8 Aug	-	X	-	1–1.5

2.1.1. UDWQ Data

UDWQ sondes were installed in a variety of locations in Utah Lake and Farmington Bay following the large July 2016 algal blooms. The site names for these sites have been modified to maintain consistency with the naming convention of the University of Utah sites. One temporary fixed sonde was placed approximately 0.75 m below the surface at station U9 (UDWQ Site 4917310) in Utah Lake, providing daily measurements between 15 July and 8 August, 2016. The sondes in stations U6 (UDWQ Site 4917390), U7 (UDWQ Site WVineyard), and U8 (UDWQ Site WProvo) were installed on buoys anchored at the locations shown in Figure 1, and provided daily measurements at approximately 0.3 m below the surface between 28 August and 13 September 2016. Water depths in Utah Lake during this time period were between 1 and 1.5 m. Finally, a fixed sonde in Farmington Bay at station FB5 (UDWQ Site 4895200) provided daily measurements between 8 July and 28 July, 2016 at a depth of approximately 0.3 m below the surface (due to extremely low water levels, which were approximately 0.5 m at this time). The measurements for these sondes (which were reported at a 15-min frequency) were averaged between 11:00–11:30 a.m. in order to maintain consistency in day-to-day comparisons (reducing the effect of diurnal patterns of algae on the chlorophyll measurements which peaks during midday and then drops in the evening). These daily measurements were used in exploring temporal variability.

2.1.2. University of Utah Data

While the fixed UDWQ sondes in Utah Lake and Farmington Bay provide stationary data for exploration of temporal variability, data collection by the University of Utah was designed to explore temporal variability as well as variability on different spatial scales. Data collected by the University of Utah was focused in the main body of the South Arm of the GSL (Gilbert Bay and Bridger Bay). Surface data at the Gilbert Bay sites were consistently collected between 9:00 and 11:30 a.m. (again, to minimize the effects of diurnal patterns of photosynthesis). Data collection took place during three periods: 6, 8, 9, 10 and 13 June; 6, 7, 8, 12 and 14 July; and 12, 15, 16, 17 and 22 August. At these sites (GB2, GB3 and GB4), approximately 20–30 measurements were taken at a 1-s frequency at an average depth of 0.4 m below the surface and averaged. The Gilbert Bay sites (prefixed with GB) which were navigable by boat, were located approximately 1000 m apart, which is the same scale as the coarsest MODIS spatial resolution. At each of these sites, data were also collected at offsets to the site center to represent sub-Landsat and sub-SENTINEL-2 resolution. These offset samples were spaced at approximately 7.5 m increments (i.e., 7.5, 15, 22.5 and 30 m) from the original sites GB2, GB3 and GB4. The offsets were identified with suffixes a, b, c and d, so that the first offset (7.5 m) from GB2 was identified as GB2a, the second offset (15 m) from GB2 was GB2b, etc.) At these sites, lake current and wind patterns differed from one sampling day to the next, resulting in variable drift directions between the GB sites and their offsets, though it was generally consistently in the southwest direction. Nonetheless, relative distances between the original sites and the offsets were maintained. Approximately 20–30 measurements at the GSL1 site were collected at a 1-s frequency approximately 0.3 m below the surface and averaged in a July sampling period (23, 24, 27, 30 and 31 July). Data collection at this site also included sampling at offsets at the same increments (7.5, 15, 22.5 and 30 m) east of the original site.

The data at Bridger Bay were averaged at approximately 0.3 m below the surface (due to low lake levels at this location), and were consistently collected in the afternoon (due to equipment availability and to reduce effect of diurnal patterns).

In addition to the surface data obtained at the Gilbert Bay sites, measurements were collected throughout the water column to examine relationships between chlorophyll measurements at different depths. At sites GB2, GB3, and GB4, data were collected over the water profile, by manually lowering the sonde at approximately 0.3 m/s and recording at a 1-s frequency. Profiles were created by averaging the concentrations over 1 m intervals from 0–6 m) to represent different ranges of the water column.

For the sites reached by boat, we approached the locations from the opposite direction of the lake current and turned off the engine, allowing the boat to drift to the sites and offsets in an effort to reduce the amount of artificial mixing caused by the engine. Despite these efforts, some amount of mixing from the engine may have occurred which would have an effect on the measured concentrations and subsequent variability, particularly near the surface. The FB site and offsets were reached by foot, and mixing may have been caused by stirring up sediments.

2.1.3. Meteorological Data

In order to examine conditions that may contribute to surface mixing in the lakes, meteorological data were collected from MesoWest weather stations located near the Gilbert Bay sampling locations (Site UT201, at 40.72255, −112.22569) and near Provo Bay in Utah Lake (Site KPVU, at 40.21667, −111.71667). Parameters including wind speed (kilometers per hour) and peak wind gust (kilometers per hour) were recorded at 10 min intervals for UT201 and at 5 min intervals for KPVU. Wind speed is averaged over a daily scale and the daily peak wind gust is the maximum peak wind gust. Daily precipitation data totals (mm) and maximum temperatures (degrees Celsius) were obtained from NOAA Stations USW00024127 at 40.7034, −112.109 and USC00427064 at 40.2458, −111.6508. Comparable meteorological data near the Farmington Bay site were not available for study period.

2.2. Statistical and Graphical Analysis

To evaluate the variation over time, we computed the autocorrelation function or estimates of autocovariance [29]. These estimates were calculated for each site with regular daily sampling (all of the UDWQ sites in Utah Lake and Farmington Bay) using the "acf" function, which is built in to the R statistical software [30]. At each of the lags for these sites, we tested for statistically significant autocovariance of surface chlorophyll measurements. The autocorrelation function could not be computed for the main GSL sites (GB and GSL), since these data were not collected at regular intervals, and there were insufficient points for alternative analyses (e.g., constructing a temporal variogram). Instead, for these sites, temporal variation was analyzed graphically by calculating the difference in chlorophyll measurements between subsequent samples (for short-term variation), as well as the mean and standard deviation for each of the sampling periods (for seasonal variation).

We also examined spatial variation of surface chlorophyll concentrations with respect to the spatial resolutions of several commonly-used sensors. As noted, the distances between sites and offsets for the samples are representative of the spatial resolution of Landsat/SENTINEL-2 and MODIS band regions. The observed differences in measurements between the offsets and the sites offer insight into fine-scale variability (<30 m) that would occur at the sub-Landsat and SENTINEL-2 spatial resolutions and coarser-scale variability (1000 m) that corresponds with the spatial resolution of MODIS. To evaluate the differences between offsets, we calculated the difference and percent differences in surface measurements between the sites and their respective offsets using Equations (1) and (2):

$$Difference = Chl_{x,j} - Chl_{y,j} \tag{1}$$

$$Percent\ Difference = \left(\frac{Chl_{x,j} - Chl_{y,j}}{Chl_{x,j}} \right) * 100 \tag{2}$$

where *Chl* is the mean chlorophyll concentration between 0 and 1 m below the surface for the sampling date j at site x (e.g., GB2) and corresponding offset y (e.g., GB2a, GB2b, etc.).

Finally, we used linear regression to evaluate relationships between conditions at the surface and throughout the water column for the GB2, GB3, and GB4 sites for each of the sampling periods. Due to extremely low lake levels in Farmington Bay, Utah Lake, and Bridger Bay, samples at multiple depths were not possible at these locations. The regressions follow the general form of Equation (3):

$$Chl_{x,k} = m \cdot Chl_{x,l} + b \tag{3}$$

where *Chl* is the mean chlorophyll concentration at site x, at depth k below the surface, and l is the depth of 0–1 m below the lake surface. The strength of the relationship is measured through the correlation coefficient, or R^2. For this case, the correlation coefficient translates to the amount of variance at intermediate depths that is explained by the surface measurements.

3. Results

3.1. Temporal Variability

The results of the autocorrelation function are visualized in a correlogram, showing the autocorrelation of surface chlorophyll values versus the lag (days). The correlograms for each of the sites with daily sampling, shown in Figure 2, graphically illustrate how the time series is correlated with itself, or how similar measurements are from one day to measurements from some lagged time period.

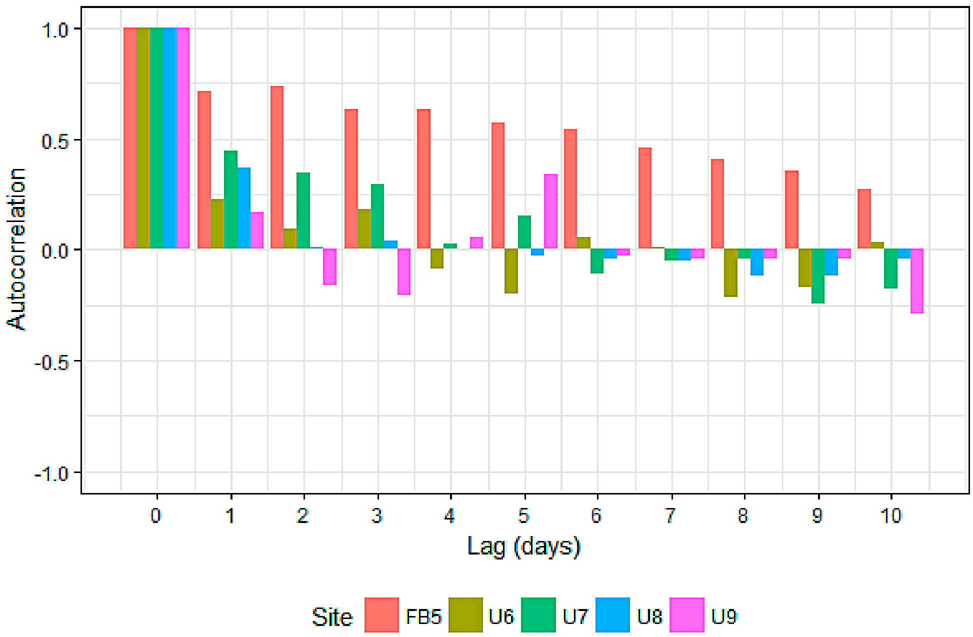

Figure 2. Autocorrelation for Utah Lake (U6, U7, U8 and U9) and Farmington Bay (FB5) Sites.

The null hypothesis, which is tested at each lag, is that there is no autocorrelation between the lagged samples. The different patterns of autocorrelation in Figure 2 show that there are major differences in the temporal autocorrelation in different parts of the lake system. At $\alpha = 0.05$, there is no statistically significant autocorrelation for all time lags for Utah Lake sites U9 and U6, and near-statistically significant autocorrelation for a lag of one day for U8 and U7. The rapid decrease in autocorrelation for many of the Utah Lake sites is evidence of high short-term variability in this body. In clear contrast with the patterns observed in Utah Lake, there is significant autocorrelation for all lags up to 11 days for the site in Farmington Bay (FB5).

For sites where it was not possible to calculate an autocorrelation function, the differences in chlorophyll measurements between subsequent samples for each of the sampling periods are shown in Figure 3.

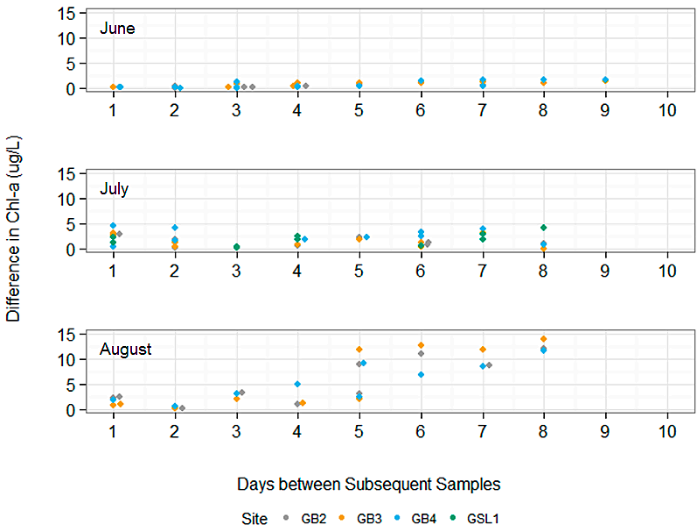

Figure 3. Temporal Variation between Subsequent Samples by Sampling Periods at the GB and GSL Sites.

In the samples from June and July, there is relatively small variation (<2 and 5 µg/L, respectively), even at 8 and 10 days between subsequent samples. In August, however, the data show a clear positive trend of increasing differences between surface chlorophyll measurements, that is, the difference between the subsequent samples increases as time between the samples increases. The data also show the variation in between subsequent measurements increases throughout the summer season. For example, in June, the mean difference at seven days between subsequent samples is 1.02 µg/L, while the mean differences in July and August at seven days are 3.05 µg/L and 9.67 µg/L, respectively. This seasonal increase in variability is also evident in comparisons of the standard deviation of surface measurements during each sampling period, shown in Figure 4. There was also a general positive trend in chlorophyll concentrations throughout the sampling period (meaning that both magnitudes of chlorophyll and variance increased throughout the summer).

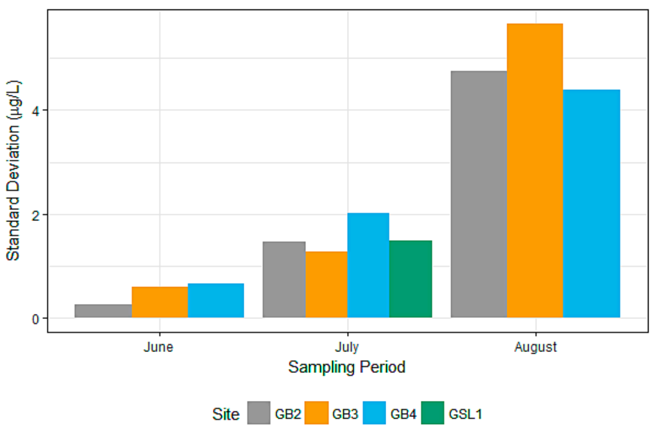

Figure 4. Standard Deviation for Surface Chlorophyll at GB and GSL Sites by Sampling Period.

3.2. Spatial Variability

To illustrate the differences in spatial resolution of several commonly-used sensors, Figure 5 compares the coverage of a portion of the study area (Utah Lake) with resolutions ranging from 30 m (Landsat 8, Band 2, 19 July 2016), to 60 m (SENTINEL-2, Band 1, 22 July 2016) and 500 m (MODIS, Band 3, 20 July 2016).

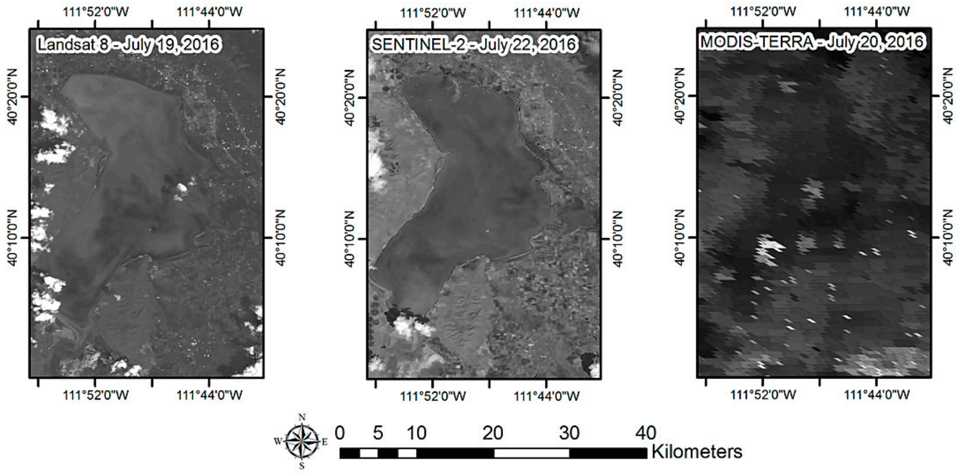

Figure 5. Comparison of Spatial Resolution in Coverage of Utah Lake at 30 m (Landsat 8, Band 2), 60 m (SENTINEL-2, Band 1) and 500 m (MODIS, Band 3).

The resolutions of Landsat and SENTINEL-2 show clear definition between the lake and the shore, and variability in surface conditions (including the extent of the large algal bloom) can be detected at both these scales. On the other hand, the coarse resolution of the MODIS image makes it difficult to delineate the shoreline and while there is some variability between the in-lake pixels, the extent of the bloom is difficult to distinguish. In the GB sites, surface chlorophyll data collected at sites and offsets correspond with the range of spatial scales for these sensors. The differences in surface chlorophyll for fine spatial scales (corresponding with Landsat/SENTINEL-2) and coarse spatial scales (corresponding with the coarsest resolution of MODIS, 1000 m) are shown in Figures 6 and 7.

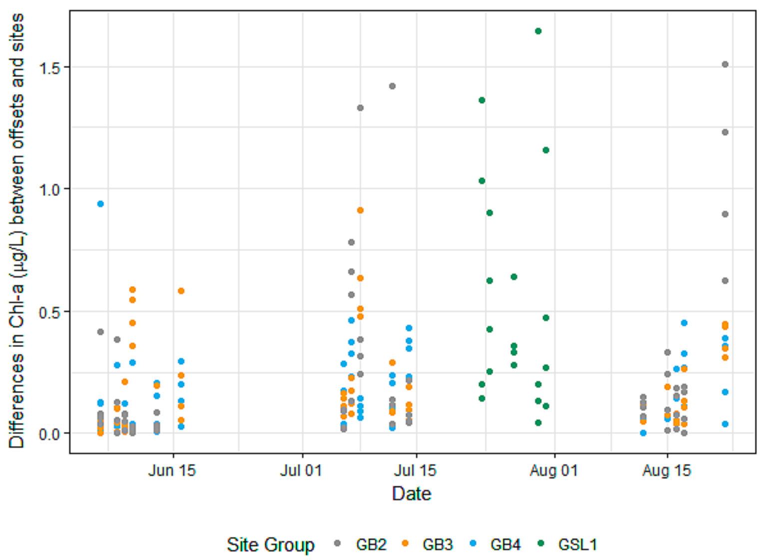

Figure 6. Variability between Sites and Offsets (<30 m distances or Sub-Landsat/Sub-SENTINEL-2 Scales) in the Great Salt Lake (GB and GSL Sites).

For site groups (where each site group includes the site and its offsets) GSL1, GB2, GB3 and GB4, there was generally less than 30 percent difference between the surface measurements at the offsets and those at the site. The plots show that the highest differences between the offsets and the sites occur in the later summer months, while relatively small differences are observed in early summer. Throughout the entire season, the maximum difference in magnitude between a site and its offsets is 1.7 µg/L.

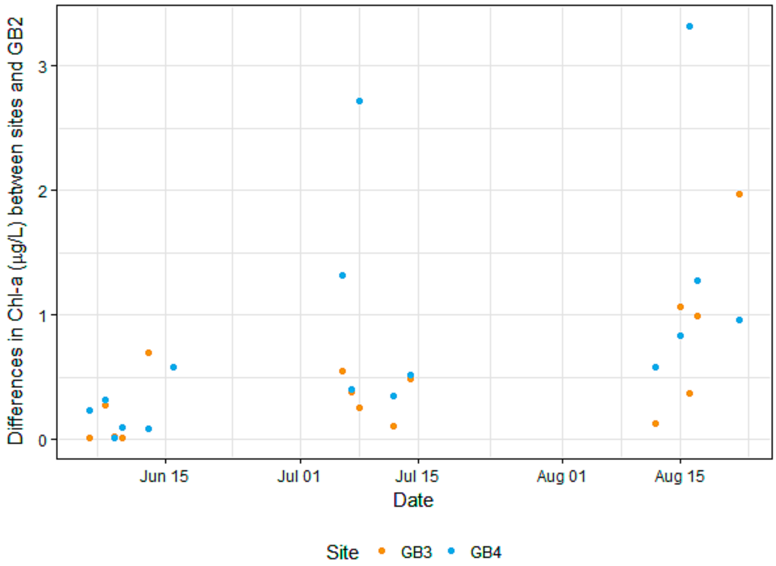

Figure 7. Variability between Sites (Approximately 1000 m distances, or MODIS Scale) in the Great Salt Lake (GB Sites).

This figure shows that even at this larger scale, the differences are still generally small (below 30 percent), though the actual difference in magnitude was higher (with a maximum difference of 3.4 µg/L) than those at the sub-pixel distances on the Landsat/SENTINEL-2 scale. Again, greater differences are observed in later summer months compared to early summer.

3.3. Surface/Water Column Measurements

The linear relationships between average surface measurements (0–1 m below the surface) and various depths (1–2 m, 2–3 m and 3–4 m) from data collected in Gilbert Bay (where water depths allowed for water column measurements) are shown in Figure 8.

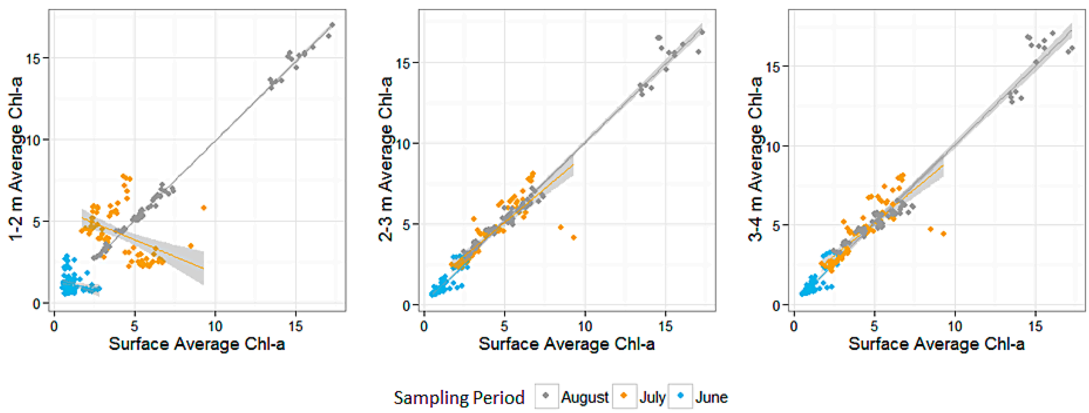

Figure 8. Relationships between Surface and Depths throughout the Water Column for GB Sites.

For 1–2 m, the overall (across all sampling periods) R^2 is 0.79; for 2–3 m it is 0.97; and for 3–4 m it is 0.96. However, the relationship is highly dependent on the sampling period, particularly at depths of 1–2 m. For June and July, there are virtually no relationships between the surface chlorophyll and chlorophyll at 1–2 m below the surface, and the relationships at other depths are weaker for these sampling periods than for the August sampling period.

3.4. Meteorological Record

Short-term weather events such as rainfall and high wind events have the potential to cause surface mixing and subsequently affect the observed temporal and spatial variability patterns, as well as conditions throughout the water column. Records of the daily average values for wind speed, peak daily wind gust, total daily precipitation and maximum temperature are shown for two weather stations near the Great Salt Lake and Utah Lake are shown in Figure 9.

During the periods of data collection for Utah Lake sites, conditions were relatively stable with respect to precipitation and temperature. The extremely shallow lake was likely heavily influenced by the wind, allowing for a great deal of mechanical mixing to occur. This corresponds with the low autocorrelation values in the Utah Lake sites. Other seasonal patterns in variability, such as the general increase in concentrations observed in the GB sites, correspond with the fairly stable and favorable weather conditions (lack of any large precipitation events during the mid-summer months, sustained high temperatures in late July, and a steady cooling through August).

The seasonality of the surface/water column relationship may be partially explained by weather conditions and short-term events, such as the variable temperature in June and July, and the slightly higher wind and precipitation events in the GSL in June. It is important to note that poor correlations between surface and 1–2 m depths may also be influenced by mechanical mixing caused by turbulence from the boat, which could create artificially high variability near the surface.

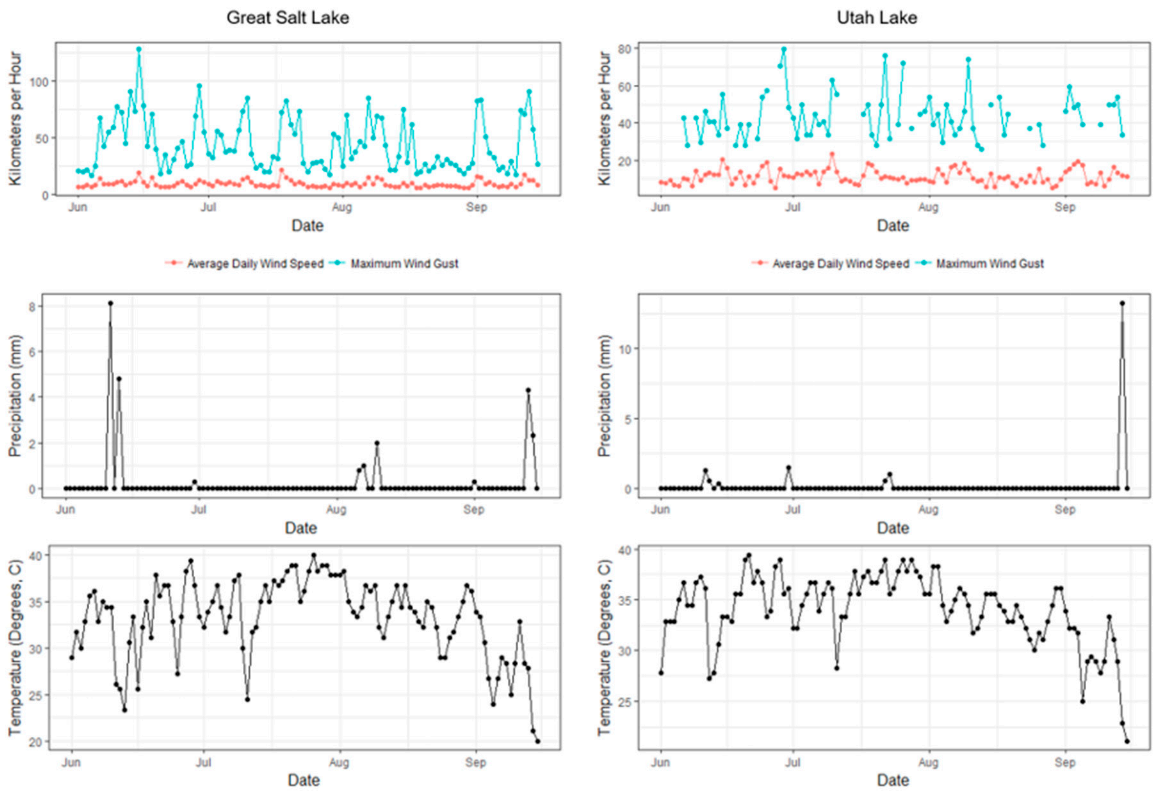

Figure 9. Daily Wind, Precipitation, and Temperature Records near the Great Salt Lake (GSL) and Utah Lake over the Period of Data Collection.

4. Discussion

The measures of variability over time (including autocorrelation, magnitude of differences between subsequent samples, and standard deviation for different sampling periods) suggest that the water bodies in the Great Salt Lake system have distinct temporal characteristics. These characteristics have important implications for remote sensing modeling techniques. The Utah Lake samples showed non-significant autocorrelation after one day, while the Farmington Bay samples showed statistically significant autocorrelation for up to 11 days. This indicates that the Utah Lake conditions are much more variable than those in Farmington Bay, with Utah Lake variation on a daily scale, rather than the near-weekly scale exhibited in Farmington Bay. In a remote sensing context, this means that shorter time windows may be needed for calibrating Utah Lake models, while longer time windows may be justified for Farmington Bay models. In the GB and GSL locations, where sampling frequencies were irregular, there was a general trend of increasing differences in chlorophyll concentrations as the time between samples increased. These differences and the overall variation increased throughout the summer, indicating that the temporal correlation may not be stationary, but decreases throughout the growing season. This increase in variability could justify a shorter time-window for near-coincident data in the later summer months than the earlier summer months.

The observed temporal patterns provide additional information for evaluating suitability of the Landsat, SENTINEL-2, and MODIS sensors for this lake system. For example, events in Utah Lake may be completely missed by the revisit time of Landsat sensors, requiring the use of multiple sensors to adequately capture the rapidly changing conditions and acknowledgment of the limitations of the temporal resolution of this sensor and its ability to describe short-term changes.

The comparisons of surface measurements between the GB and GSL sites and offsets as well as among sites were also useful in evaluating different spatial resolutions of commonly-used sensors. The relatively small variation between sites and offsets indicates that there is low variability over the distances measured by a single pixel for Landsat/SENTINEL-2 or MODIS. This suggests that these platforms, or others with similar spatial resolution, are suitable for monitoring the main body of the GSL. These results also suggest that finer spatial resolution products (such as those obtained by airborne sensors) would not necessarily provide significantly more information for this part of the system.

Finally, the linear models between concentrations at the surface and those at different depths in the water column in the GB sites show that these relationships are both depth and seasonally dependent. This result is interesting because it shows a stronger relationship between the measurements at the surface and greater depths (2–3 and 3–4 m) than between the surface and subsurface (1–2 m) measurements. If the data are analyzed by sampling period, the relationship between the surface data and the 1–2 m data exhibit a relatively strong fit for August, but not in June or July. The data at greater depths, however, exhibit relatively strong relationships during all of the sampling periods. The high variability observed at the surface and near-surface depths indicates that surface-biased estimates may be influenced by short-term weather events or human activity that causes mixture. The strong linear relationships for the other depths and for 1–2 m depths during August suggest that near-surface estimates provided by remote sensing may be strongly correlated with conditions throughout the water column, especially during periods of low surface mixing. In summary, the different relationships between surface and water column conditions highlight that surface conditions do not always reflect the conditions throughout the water column, and that the mechanical mixing processes which are unique to each water body should be taken into account before assuming any relationship between surface and water column conditions.

The spatial and temporal patterns observed in these lakes add to previous observational studies in these lakes which have focused largely on speciation and the diversity of algal populations. As species diversity decreases throughout the summer, the observations in this study also show that overall algae biomass magnitudes and variability in algae biomass increases. This relationship has both positive and negative implications for remote sensing; it provides additional motivation for using remote sensing methods during the late summer months when conditions are highly variable and more likely to be worse than early summer months, but it also highlights potential challenges associated with remote sensing of conditions when there is high species variability (leading to greater potential variability in the spectral signature of the surface waters).

5. Conclusions

The observations and analysis provided valuable insights into the Utah and GSL lake systems; however, it is important to acknowledge that the results may not be representative for all portions of the system. In particular, the surface/water column analyses in the lower portion of the GSL are not representative of the surface water/water column relationship in Utah Lake. Utah Lake is consistently much more turbid than the southern arm of the GSL, in general is shallower, and has far different mixing patterns. We recommend that this kind of analysis should be conducted in areas where unique or localized hydrodynamic disturbances exist (such as elevated exposure to wind and surface mixing, or near outfalls from wastewater treatment plants or streams where there may be increased mixing or stirring up of bottom sediments).

The temporal and spatial analysis presented in this study supports development of specific methods for future remote sensing work in this region. This support includes selecting appropriate sensors and defining appropriate time-windows for using near-coincident data. The seasonal differences in temporal correlation (as inferred by differences between subsequent samples) suggest the use of a shorter time-window for near-coincident data in calibrating empirical models in the late summer season than in the earlier summer months. We recommend that for modeling development in the main body of the GSL, near-coincident matches be limited to ± 2 days, though more relaxed time-windows could be used for early summer matches. Based on the autocorrelation of the samples in Utah Lake and Farmington Bay, we recommend limiting the time windows for considering near-coincident matches to ± 1 day for Utah Lake, while Farmington Bay may use a more relaxed time window.

Our spatial analysis showed small variations between offsets and sampling sites, indicating that Landsat/SENTINEL-2 resolution and MODIS resolutions would be appropriate for the southern arm of GSL, while finer-scale resolutions may be unnecessary as there is little variation at these smaller scales. As with the surface/water column analysis, this type of sampling in other parts of the lake system would be helpful in determining the most appropriate methods based on their unique spatial variability characteristics. From a temporal standpoint, the Landsat return time of 16 days is offset by the fact that there are multiple sensors which may be used, for example both Landsat 5 and 7 provide data for historical applications, while Landsat 8 and SENTINEL-2 provide data for more recent and ongoing applications (from 2013 and 2015, respectively). These instruments provide imagery on a more frequent basis (assuming no interference from cloud cover). However, our temporal analysis of the sensor data in Utah Lake and the main body of the GSL, shows that lake conditions change on shorter periods, and this revisit frequency may miss important changes in surface algae conditions. This is contrasted by Farmington Bay, where the conditions do not change as drastically over these time scales.

The information about spatiotemporal patterns should be considered along with other factors including: the spectral resolution of the sensors and how well the spectral measurements can describe the measures of algal biomass in certain lake environments [31], data availability (both field samples and imagery), and the historical scope (which may restrict the types of sensors which can be used) in order to meet the needs of the specific region of interest and the application. While focused on the GSL region and its unique characteristics, this study demonstrates a number of sampling and analysis techniques that could be applied in other settings to inform and improve the design of remote sensing studies. Information about the unique spatial and temporal variability patterns in a water body should be incorporated into the process of remote sensing model development, to help guide modeling decisions and assumptions.

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References

1. Olmanson, L.G.; Bauer, M.E.; Brezonik, P.L. A 20-year Landsat water clarity census of Minnesota's 10,000 lakes. *Remote Sens. Environ.* **2008**, *112*, 4086–4097. [CrossRef]
2. Kloiber, S.M.; Brezonik, P.L.; Olmanson, L.G.; Bauer, M.E. A procedure for regional lake water clarity assessment using Landsat multispectral data. *Remote Sens. Environ.* **2002**, *82*, 38–47. [CrossRef]
3. Sayers, M.; Fahnenstiel, G.L.; Shuchman, R.A.; Whitley, M. Cyanobacteria blooms in three eutrophic basins of the great lakes: A comparative analysis using satellite remote sensing. *Int. J. Remote Sens.* **2016**, *37*, 4148–4171. [CrossRef]
4. Hansen, C.H.; Williams, G.P.; Adjei, Z.; Barlow, A.; Nelson, E.J.; Miller, A.W. Reservoir water quality monitoring using remote sensing with seasonal models: Case study of five central-Utah reservoirs. *Lake Reserv. Manag.* **2015**, *31*, 225–240. [CrossRef]
5. Wynne, T.T.; Stumpf, R.P.; Tomlinson, M.C.; Fahnenstiel, G.L.; Dyble, J.; Schwab, D.J.; Joshi, S.J. Evolution of a cyanobacterial bloom forecast system in western Lake Erie: Development and initial evaluation. *J. Gt. Lakes Res.* **2013**, *39*, 90–99. [CrossRef]
6. Glasgow, H.B.; Burkholder, J.M.; Reed, R.E.; Lewitus, A.J.; Kleinman, J.E. Real-time remote monitoring of water quality: A review of current applications, and advancements in sensor, telemetry, and computing technologies. *J. Exp. Mar. Biol. Ecol.* **2004**, *300*, 409–448. [CrossRef]
7. Goldman, C.R.; Jassby, A.D.; Hackley, S.H. Decadal, interannual, and seasonal variability in enrichment bioassays at Lake Tahoe, California-Nevada, USA. *Can. J. Fish. Aquat. Sci.* **1993**, *50*, 1489–1496. [CrossRef]
8. Jiang, Y.-J.; He, W.; Liu, W.-X.; Qin, N.; Ouyang, H.-L.; Wang, Q.-M.; Kong, X.-Z.; He, Q.-S.; Yang, C.; Yang, B. The seasonal and spatial variations of phytoplankton community and their correlation with environmental factors in a large eutrophic Chinese lake (Lake Chaohu). *Ecol. Indic.* **2014**, *40*, 58–67. [CrossRef]
9. Wynne, T.T.; Stumpf, R.P. Spatial and temporal patterns in the seasonal distribution of toxic cyanobacteria in western Lake Erie from 2002–2014. *Toxins* **2015**, *7*, 1649–1663. [CrossRef] [PubMed]
10. Mouw, C.B.; Greb, S.; Aurin, D.; DiGiacomo, P.M.; Lee, Z.; Twardowski, M.; Binding, C.; Hu, C.; Ma, R.; Moore, T. Aquatic color radiometry remote sensing of coastal and inland waters: Challenges and recommendations for future satellite missions. *Remote Sens. Environ.* **2015**, *160*, 15–30. [CrossRef]
11. Bailey, S.W.; Werdell, P.J. A multi-sensor approach for the on-orbit validation of ocean color satellite data products. *Remote Sens. Environ.* **2006**, *102*, 12–23. [CrossRef]
12. Giardino, C.; Pepe, M.; Brivio, P.A.; Ghezzi, P.; Zilioli, E. Detecting chlorophyll, Secchi Disk Depth and surface temperature in a sub-alpine lake using Landsat imagery. *Sci. Total Environ.* **2001**, *268*, 19–29. [CrossRef]
13. Lesht, B.M.; Barbiero, R.P.; Warren, G.J. A band-ratio algorithm for retrieving open-lake chlorophyll values from satellite observations of the great lakes. *J. Gt. Lakes Res.* **2013**, *39*, 138–152. [CrossRef]
14. McCullough, I.M.; Loftin, C.S.; Sader, S.A. Landsat imagery reveals declining clarity of Maine's lakes during 1995–2010. *Freshw. Sci.* **2013**, *32*, 741–752. [CrossRef]
15. Johnson, R.; Strutton, P.G.; Wright, S.W.; McMinn, A.; Meiners, K.M. Three improved satellite chlorophyll algorithms for the southern ocean. *J. Geophys. Res. Oceans* **2013**, *118*, 3694–3703. [CrossRef]
16. Olmanson, L.G.; Brezonik, P.L.; Bauer, M.E. Evaluation of medium to low resolution satellite imagery for regional lake water quality assessments. *Water Resour. Res.* **2011**, *47*. [CrossRef]
17. Meuser, J.E.; Baxter, B.K.; Spear, J.R.; Peters, J.W.; Posewitz, M.C.; Boyd, E.S. Contrasting patterns of community assembly in the stratified water column of Great Salt Lake, Utah. *Microb. Ecol.* **2013**, *66*, 268–280. [CrossRef] [PubMed]

18. Klausmeier, C.A.; Litchman, E. Algal games: The vertical distribution of phytoplankton in poorly mixed water columns. *Limnol. Oceanogr.* **2001**, *46*, 1998–2007. [CrossRef]
19. Goel, R.; Myers, L. Evaluation of cyanotoxins in the Farmington Bay, Great Salt Lake, Utah. Available online: http://cdsewer.org/GSLRes/2009_CYANOBACTERIA_PROJECT_REPORT.pdf (accessed on 1 January 2016).
20. Marden, B.; Richards, D. Factors Influencing Cyanobacteria Blooms in Farmington Bay, Great Salt Lake, Utah. Available online: https://www.researchgate.net/profile/David_Richards20/publication/305488678_Factors_Influencing_Cyanobacteria_Blooms_in_Farmington_Bya_Great_Salt_Lake_Utah/links/5790eefe08ae0831552f92ab.pdf (accessed on 12 March 2015).
21. Rushforth, S.R.; Squires, L.E. New records and comprehensive list of the algal taxa of Utah Lake, Utah, USA. *Gt. Basin Nat.* **1985**, *45*, 237–254.
22. Whiting, M.C.; Brotherson, J.D.; Rushforth, S.R. Environmental interaction in summer algal communities of Utah Lake. *Gt. Basin Nat.* **1978**, *38*, 31–41.
23. Wurtsbaugh, W.A.; Marcarelli, A.M.; Boyer, G.L. Eutrophication and Metal Concentrations in Three bays of the Great Salt Lake (USA). Available online: http://digitalcommons.usu.edu/cgi/viewcontent.cgi?article=1548&context=wats_facpub (accessed on 1 July 2012).
24. Naftz, D.; Angeroth, C.; Kenney, T.; Waddell, B.; Darnall, N.; Silva, S.; Perschon, C.; Whitehead, J. Anthropogenic influences on the input and biogeochemical cycling of nutrients and mercury in Great Salt Lake, Utah, USA. *Appl. Geochem.* **2008**, *23*, 1731–1744. [CrossRef]
25. USGS. Great Salt Lake—Salinity and Water Quality. Available online: https://ut.water.usgs.gov/greatsaltlake/salinity/ (accessed on 5 April 2017).
26. Wurtsbaugh, W.; Marcarelli, A. *Eutrophication in Farmington Bay, Great Salt Lake, Utah 2005 Annual Report*; Central Davis Sewer District: Kaysville, UT, USA, 2006.
27. Utah DEQ. *Utah Lake Report*; Utah Department of Environmental Quality: Salt Lake City, UT, USA, 2006.
28. Hansen, C. *Great Salt Lake Water Quality*; Hydroshare: Cambridge, MA, USA, 2017.
29. Cressie, N.; Wikle, C.K. *Statistics for Spatio-Temporal Data*; John Wiley & Sons: Hoboken, NJ, USA, 2015.
30. R Core Team. *R: A Language and Environment for Statistical Computing*; R Foundation for Statistical Computing: Vienna, Austria, 2016.
31. Olmanson, L.G.; Brezonik, P.L.; Finlay, J.C.; Bauer, M.E. Comparison of Landsat 8 and Landsat 7 for regional measurements of CDOM and water clarity in lakes. *Remote Sens. Environ.* **2016**, *185*, 119–128. [CrossRef]