Long-Term Spatiotemporal Monitoring and Analysis

of Chlorophyll-a concentrations in Utah Lake

Kaylee Tanner, Anna Cardall, and Gustavious Williams

Brigham Young University

1. Introduction

1.1 Utah Lake and HABs

Utah Lake is a unique and valuable natural resource in the semi-arid Utah Valley. Shallow, turbid, eutrophic, and slightly saline, the lake degrades and stabilizes pollution well [1]. The lake is a highly productive ecosystem and provides ecological habitats, water storage, and recreation. Detection of harmful algal blooms (HABs), however, has closed Utah Lake beaches every summer since 2016 [2] and raised concerns over the health of the lake ecosystem [3, 4]. HABs, which involve excessive algal growth that can cause hypoxic and/or toxic water conditions [5], have numerous detrimental effects [6] on lakes and reservoirs in the United States and throughout the world [7, 8]. They are most prevalent during warm periods, and studies indicate that global climate change could be a catalyst for these blooms [8, 9] as lake and reservoir surface temperatures increase [10, 11]. Utah Lake experiences intense blooms with severe consequences for recreational revenue and downstream agriculture.

Although alarm over HABs has spiked worldwide [12, 13], algal blooms, which are characteristic of eutrophic conditions [3, 13], are not a new phenomenon on Utah Lake [14], which experiences nutrient loadings tens-of-times larger than those that would designate the lake as eutrophic [1] [15]. Analysis of historical water quality trends on Utah Lake can help determine whether algal blooms are occurring more frequently, and provide insight into the debate over how controls on nutrient inflows to the lake affect water quality [16].

1.2 Mitigation Efforts

Water managers are currently investigating various mitigation actions to improve the water quality of Utah Lake, with a focus on algal blooms. Proposed actions include more restrictive guidelines on sewage treatment plants and other nutrient sources, which would be very expensive to implement. There is some debate on whether nutrient inflows drive the algal blooms, or if nutrient levels in the lake are maintained by sediment and dust inputs [16-18]. If the latter, restrictions on nutrient inflows may have limited impacts on algal blooms and other water quality issues. The better we understand historical water quality and algal bloom trends, the better we can predict the success of potential mitigation measures.

Remotely sensed data from the Landsat missions are available starting in 1984 at 16-day intervals (weather and equipment permitting). We used these images to develop a time-history of algal blooms in Utah Lake, which will help us analyze whether changes in nutrient inflows have a major impact on algal blooms.

As some researchers have argued that the increasing frequency of HABs worldwide is due to human activity [5], there is interest in work that will improve our understanding of how human populations influence HABs [5, 19]. We hypothesize that nutrient loads to Utah Lake in 1984 were significantly lower than the current loads, in part because the population surrounding the lake has increased by 300% since the 1980s, and that trends in algal concentrations in Utah Lake as estimated by Landsat data can be used to assess the impact of nutrient inflows and predict the success of mitigation strategies focused on reducing nutrient inflow.

1.3 Remote Sensing of Algae Blooms

Remote sensing has been used extensively since the 1970’s to monitor water quality [5, 14], as it can successfully estimate measures of water quality such as clarity, chlorophyll-a (chl-a), and temperature. [20-22]. The Landsat series of satellites, which we use for this study, are popular in water quality research, as they have a relatively high spatial resolution (approximately 30m per pixel) and short revisit time (16 days), as well as a selection of spectral bands designed for vegetation and water quality studies.

Traditionally, most Landsat water quality studies relied on field data taken coincident with the satellite overpass and an empirical equation to estimate chl-*a* concentration from the image [23, 24]. This limited analysis to only those images with associated ground truth. Recently, researchers have shown that non-coincident data can be used to develop accurate chlorophyll models that successfully estimate chl-*a* concentrations in historical images [25-27]. Researchers have also shown that, because different algal populations dominate during different seasons [28], seasonal models developed and applied to the full time-series of Landsat images yield even more accurate estimations of algal concentrations [27, 29].

We used these findings and the ability of remote sensing data to reveal spatial distributions [30] and long term trends [22] to create and analyze a time history of algal blooms in Utah Lake. We can then use that time history to examine water quality trends and evaluate to what extent those trends are correlated with population growth in Utah County, which is an index to nutrient loads from sewage treatment plants into Utah Lake. Since we don't have a convenient stash of spatially and temporally comprehensive water sampling data going all the way back to 1984, remotely sensed data is the only way to look back in time and conduct this analysis.

Remote sensing of water quality does have limitations, with the most important being the difficulty of extracting accurate estimations of chl-*a* concentrations from the images. This is a difficult process due to factors like cloud cover, complex water optical properties (especially in turbid waterbodies like Utah Lake) [31], and the challenge of differentiating between dense algae blooms and land vegetation [32, 33]. Much research has been done to address these issues [34-38], which we will rely on in this study, and our choice to use primarily the Google Earth Engine (GEE) platform for this analysis greatly simplifies the work required to process the Landsat images [39].

2. Methods

2.1 Chlorophyll Estimate Models

Chl-a concentrations estimated through model application may not be precise due to the difficulties previously mentioned, but changes in concentration over time and spatial distributions are relatively accurate [27], so our results will be valid insight into water quality trends in Utah Lake.

The following is a brief summary of the GEE code used to calculate chl-*a* concentration values from the Landsat imagery.

The first step in the analysis is creating a time-series image collection with the data from Landsat 5, 7, and 8. Then a mask is applied to each image to discard land pixels, so that only pixels containing lake water are included in the analysis. We used the Modified Normalized Difference Water Index (MNDWI) for this mask [40], as a recent study found it was the most successful at differentiating between land and lake water on Utah Lake, even in areas with high algae concentrations [33]. We also added a data quality mask to eliminate pixels with cloud cover, scan line errors, and other issues, which will improve the quality of our analysis. Using these quality controlled, water-only images, we can apply the chl-*a* models, which are band functions [29], to estimate the chl-a concentration in each pixel. The resulting pixel values can then be displayed as an image, an example of which is shown in Figure 1, which provides a visual map of spatial variation in chl-a concentrations throughout the lake. Figure 1 also demonstrates how pixels contaminated

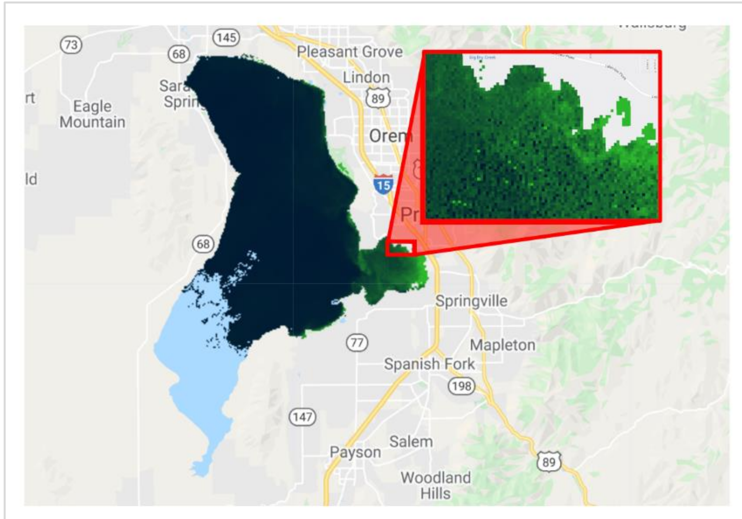


Figure 1: pixel concentrations of chl-a in µg/L, with lighter green representing higher concentrations

with cloud cover at the lower end of the lake were excluded from the analysis by the quality mask.

2.2. *Trend Analysis*

To discern trends in HABs on Utah Lake, we apply the Mann-Kendall (M-K) test [41] to the seasonal image collections. This non-parametric statistical test, which is ideal for this analysis because it is not affected by missing data or the data distribution, reveals consistently increasing or decreasing trends and the statistical significance of those trends. The M-K test is commonly used to identify monotonic trends in environmental, climate, and hydrologic data and is recommended by the US EPA National Nonpoint Source Monitoring Program [42].

For the M-K test, the null hypothesis, H_0, is that the data come from a population with independent realizations and are identically distributed. The alternative hypothesis, H_A, is that the data follow a monotonic trend. The Mann-Kendall test statistic is calculated according to:

$$S = \sum_{k=1}^{n-1} \sum_{j=k+1}^{n} sgn(X_j - X_k)$$

With:

$$sgn(x) = \begin{cases} 1 & if\ x > 0 \\ 0 & if\ x = 0 \\ -1 & if\ x < 0 \end{cases}$$

When S is a large positive number, later-measured values tend to be larger than earlier values, indicating an upward trend. When S is a large negative number, later values tend to be smaller than earlier values, indicating a downward trend. A small absolute value of S indicates no trend. The M-K test statistic, used to determine if the trend is statistically significant, is computed as:

$$\tau = \frac{S}{n(n-1)/2}$$

which has a range of –1 to +1 and is analogous to the correlation coefficient in regression
analysis.

The null hypothesis of no trend is rejected when S and τ are significantly
different from zero. If a significant trend is found, the rate of change can be calculated
using the Sen slope estimator [43]:

$$\beta_1 = median\left(\frac{y_j - y_i}{x_j - x_i}\right)$$

for all i < j and i = 1, 2, …, n-1 and j = 2, 3,…, n. In other words, the Sen slope estimator is the median slope for all pairs of data that were used to compute S.

3. Results

For the preliminary analysis, we focused on 2 main datasets generated by the GEE code: the whole-lake median for each image, and the individual pixel values. For both of these datasets we ran the M-K test to identify temporal trends and whether or not they were statistically significant.

3.1 Whole-lake Median

Figure 2 represents the whole-lake median chl-*a* concentration values from 1984-2021 shown as a line graph.

as there is little algae during these months and ice or snow results in unreliable estimates. Any given image most likely has pixels that are masked because of clouds or other quality issues. There may be complete cloud cover for some images, meaning these data are also not included. If all the data for a given date is missing, the graph linearly connects the data points on either side. This can happen when clouds cover the region. Graphs such as this provide researchers and managers with a better understanding of the lake and how it has changed over time. While visually there is a slight apparent upward trend in the graph, the Mann-Kendall results for this dataset indicate the trend is not statistically significant.

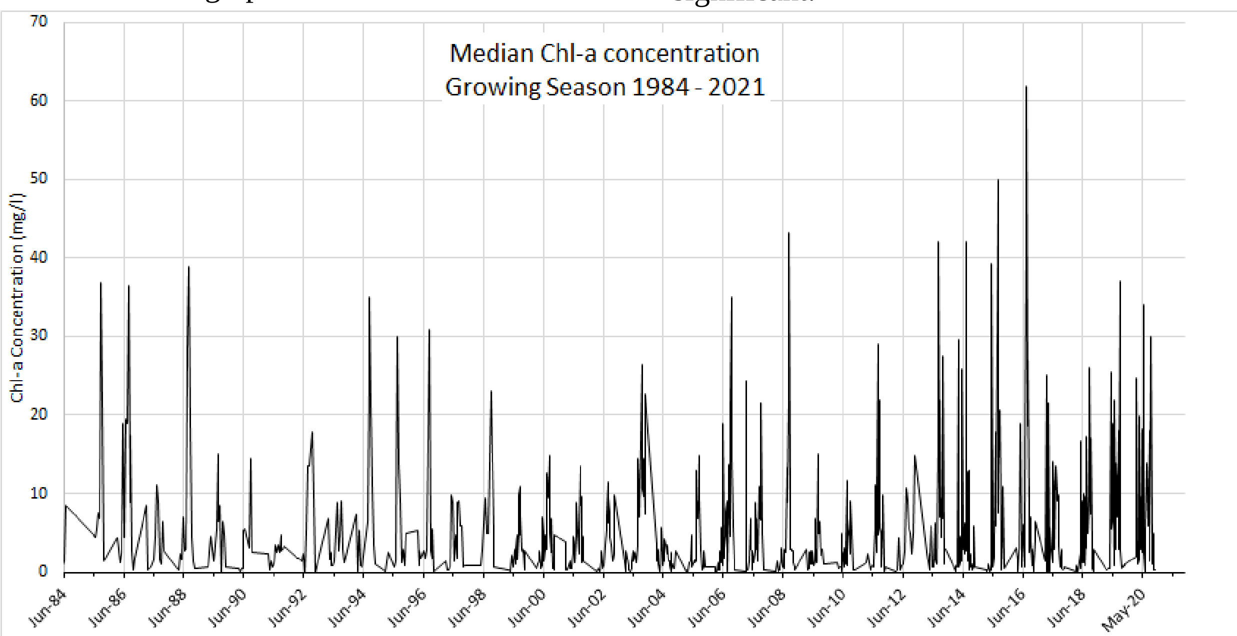


Figure 2: Median chl-a values for the entire Utah Lake from 1984–2021. This chart does not include data for November, December, January, or February. The figure shows that chl-a levels typically peak in July, just after the tic-mark representing June.

Each point on the graph represents the median chl-*a* value for the entire lake on that date, and there is a data point approximately every 16 days during the growing season. In some cases, there is less time between images because of overlap between the satellites, and the graph does not include data from November, December, January, or February,

3.2 Individual Pixels

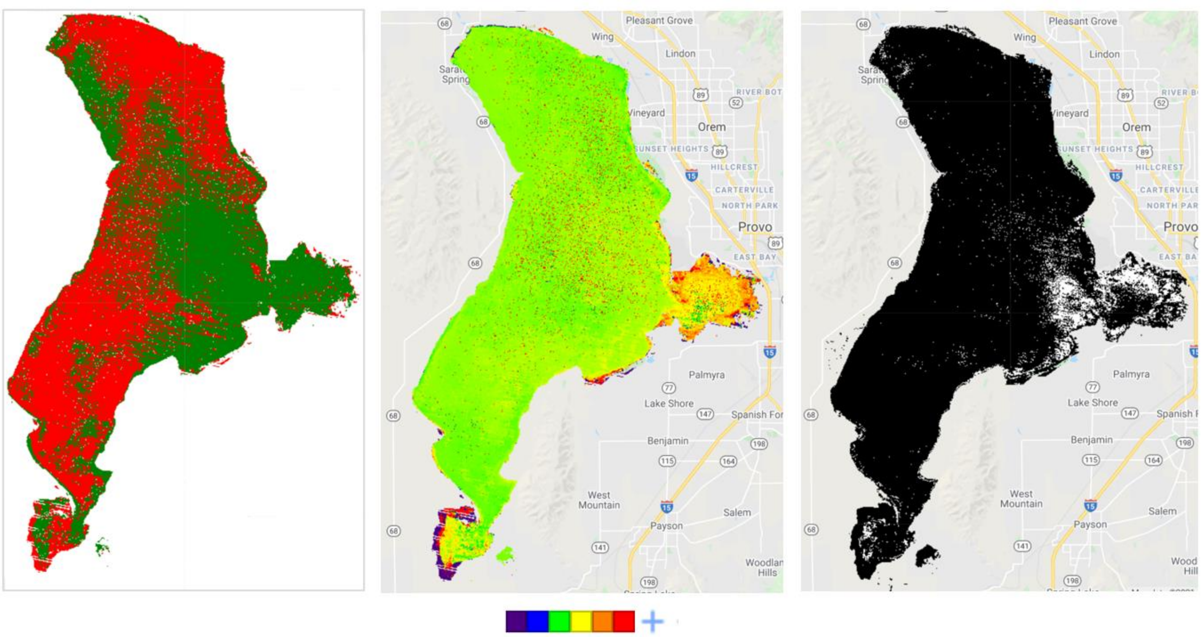
Due to processing constraints, we were unable to perform the M-K test on the entire time series within the GEE environment, so this paper presents a subset of 31 images taken during the month of July during the years 1999-2010. We selected the month of

July because the whole-lake median trends indicated that algal blooms typically peak in July. Figure 3 shows a preliminary example of the results of this analysis. In image (a), red represents a downward trend, and green represents an upward trend for each respective pixel over the time series. In image (b), warm colors represent a trend with a large magnitude, and cooler colors represent trends with a smaller magnitude. Image (c) shows the statistical significance of those trends, with white representing a statistically significant trend for that pixel.

which affected all images collected by Landsat 7 after May 31, 2003. We will also implement seasonal chl-*a* models to improve the accuracy of the algal concentration estimates.

4. Conclusion

Using the Mann Kendall test on the whole-lake and small area median values as well as the individual pixel values allows us to observe spatial and temporal trends in algal concentrations in Utah Lake with a high level of detail and accuracy. We can then compare those trends with the external factors suspected of influencing HABs. Besides comparing the results with the most obvious factor of population change, we are also interested in examining how other land-use changes, such as the Provo Bay restoration, may influence algae blooms. We hope that this research will contribute to a better scientific understanding of Utah Lake and promote the use of remote sensing as a tool for informing water management.



(a) (b) (c)

Figure 3: Results of the Mann-Kendall test on a time series of 31 July images from 1999-2010

This visual representation of algae concentrations and trends aligns well with what we already know of Utah Lake ecology: that the hydrologically isolated Provo Bay and the eastern shoreline of Utah Lake are “hot spots” for algae blooms [33], while algal concentrations in the middle of the lake are typically lower. Before we can draw any meaningful conclusions; however, the code needs some adjustments, including the addition of a pixel quality mask and a mask to account for the Scan Line Corrector error,

1. Williams, G.P., *Great Salt Lake and Utah Lake Statistical Analysis: Vol II: Utah Lake*. 2020.
2. *Harmful Algal Blooms Home - Utah Department of Environmental Quality*. 2021.
3. Alsanea, A., *A Holistic Approach to Cyanobacterial Harmful Algal Blooms in Shallow, Eutrophic Utah Lake*. 2018, The University of Utah: Ann Arbor. p. 60.
4. Christoffersen, K., *Ecological implications of cyanobacterial toxins in aquatic food webs.* Phycologia, 1996. **35**(sup6): p. 42-50.
5. Sellner, K.G., G.J. Doucette, and G.J. Kirkpatrick, *Harmful algal blooms: causes, impacts and detection.* Journal of Industrial Microbiology and Biotechnology, 2003. **30**(7): p. 383-406.
6. Carmichael, W.W., *Health Effects of Toxin-Producing Cyanobacteria: "The CyanoHABs".* Human and Ecological Risk Assessment: An International Journal, 2001. **7**(5): p. 1393-1407.
7. Johnston, B.R. and J.M. Jacoby, *Cyanobacterial toxicity and migration in a mesotrophic lake in western Washington, USA.* Hydrobiologia, 2003. **495**(1/3): p. 79-91.
8. Paerl, H.W. and J. Huisman, *Climate change: a catalyst for global expansion of harmful cyanobacterial blooms.* Environmental Microbiology Reports, 2009. **1**(1): p. 27-37.
9. Jöhnk, K.D., et al., *Summer heatwaves promote blooms of harmful cyanobacteria.* Global Change Biology, 2008. **14**(3): p. 495-512.
10. Sharma, S., et al., *A global database of lake surface temperatures collected by in situ and satellite methods from 1985–2009.* Scientific Data, 2015. **2**(1): p. 150008.
11. Straile, D., *Meteorological forcing of plankton dynamics in a large and deep continental European lake.* Oecologia, 2000. **122**(1): p. 44-50.
12. Paerl, H.W. and V.J. Paul, *Climate change: Links to global expansion of harmful cyanobacteria.* Water Research, 2012. **46**(5): p. 1349-1363.
13. Anderson, D.M., P.M. Glibert, and J.M. Burkholder, *Harmful algal blooms and eutrophication: Nutrient sources, composition, and consequences.* Estuaries, 2002. **25**(4): p. 704-726.
14. Strong, A.E., *Remote sensing of algal blooms by aircraft and satellite in Lake Erie and Utah Lake.* Remote Sensing of Environment, 1974. **3**(2): p. 99-107.
15. Merritt, L.B., *Open Letter to the Utah Lake Science Panel & Lake Steering Committee*. 2020.
16. Randall, M.C., et al. *Sediment potentially controls in-lake phosphorus cycling and harmful cyanobacteria in shallow, eutrophic Utah Lake*. PloS one, 2019. **14**, e0212238 DOI: 10.1371/journal.pone.0212238.
17. Williams, G.P., et al. *Phosphorus Distribution in Reservoir Sediments: Implications for Groundwater Transport*. in *World Environmental and Water Resources Congress 2010*. 2010. American Society of Civil Engineers.
18. Olsen, J., et al., *Measuring and Calculating Current Atmospheric Phosphorous and Nitrogen Loadings to Utah Lake Using Field Samples and Geostatistical Analysis.* Hydrology, 2018. **5**(3): p. 45.
19. Paerl, H.W. and T.G. Otten, *Harmful Cyanobacterial Blooms: Causes,*

Consequences, and Controls. Microbial Ecology, 2013. **65**(4): p. 995-1010.

20. Kloiber, S.M., et al., *A procedure for regional lake water clarity assessment using Landsat multispectral data.* Remote Sensing of Environment, 2002. **82**(1): p. 38-47.
21. Fuller, L.M., S.S. Aichele, and R.J. Minnerick, *Predicting water quality by relating secchi-disk transparency and chlorophyll a measurements to satellite imagery for Michigan Inland Lakes, August 2002*, in *Scientific Investigations Report*. 2004: Reston, VA.
22. Olmanson, L.G., M.E. Bauer, and P.L. Brezonik, *A 20-year Landsat water clarity census of Minnesota's 10,000 lakes.* Remote Sensing of Environment, 2008. **112**(11): p. 4086-4097.
23. Le, C., et al., *Remote sensing of phycocyanin pigment in highly turbid inland waters in Lake Taihu, China.* International Journal of Remote Sensing, 2011. **32**(23): p. 8253-8269.
24. Gons, H.J., *Optical Teledetection of Chlorophyllain Turbid Inland Waters.* Environmental Science & Technology, 1999. **33**(7): p. 1127-1132.
25. Hansen, C.H., et al., *Evaluating historical trends and influences of meteorological and seasonal climate conditions on lake chlorophyll a using remote sensing.* Lake and Reservoir Management, 2019. **36**(1): p. 45-63.
26. Hansen, C.H., G.P. Williams, and Z. Adjei, *Long-Term Application of Remote Sensing Chlorophyll Detection Models: Jordanelle Reservoir Case Study.* Natural Resources, 2015. **06**(02): p. 123-129.
27. Hansen, C.H., et al., *Reservoir water quality monitoring using remote sensing with seasonal models: case study of five central-Utah reservoirs.* Lake and Reservoir Management, 2015. **31**(3): p. 225-240.
28. Castenholz, R.W., *SEASONAL CHANGES IN THE ATTACHED ALGAE OF FRESHWATER AND SALINE LAKES IN THE LOWER GRAND COULEE, WASHINGTON1.* Limnology and Oceanography, 1960. **5**(1): p. 1-28.
29. Hansen, C., et al., *Development of Sub-Seasonal Remote Sensing Chlorophyll-A Detection Models.* American Journal of Plant Sciences, 2013. **04**(12): p. 21-26.
30. Nelson, S.A.C., et al., *Regional assessment of lake water clarity using satellite remote sensing.* Journal of Limnology, 2003. **62**(1s): p. 27.
31. Bertani, I., et al., *Tracking cyanobacteria blooms: Do different monitoring approaches tell the same story?* Science of The Total Environment, 2017. **575**: p. 294-308.
32. Kutser, T., *Quantitative detection of chlorophyll in cyanobacterial blooms by satellite remote sensing.* Limnology and Oceanography, 2004. **49**(6): p. 2179-2189.
33. Tate, R.S., *Landsat collections reveal long-term algal bloom hot spots of Utah Lake*. viii, 47 pages.
34. Augusto-Silva, P., et al., *Analysis of MERIS Reflectance Algorithms for Estimating Chlorophyll-a Concentration in a Brazilian Reservoir*. Remote Sensing, 2014. **6**(12): p. 11689-11707.
35. Brezonik, P., K.D. Menken, and M. Bauer, *Landsat-based Remote Sensing of Lake Water Quality Characteristics, Including Chlorophyll and Colored Dissolved*

Organic Matter (CDOM). Lake and Reservoir Management, 2005. **21**(4): p. 373-382.
36. Cox, R.M., et al., *Assessing Water Quality in Catawba River Reservoirs Using Landsat Thematic Mapper Satellite Data*. Lake and Reservoir Management, 1998. **14**(4): p. 405-416.
37. Ho, J.C. and A.M. Michalak, *Challenges in tracking harmful algal blooms: A synthesis of evidence from Lake Erie*. Journal of Great Lakes Research, 2015. **41**(2): p. 317-325.
38. Shi, K., et al., *Remote sensing of cyanobacterial blooms in inland waters: present knowledge and future challenges*. Science Bulletin, 2019. **64**(20): p. 1540-1556.
39. Hansen, C., *Google Earth Engine as a Platform for Making Remote Sensing of Water Resources a Reality for Monitoring Inland Waters*. 2015.
40. Xu, H., *Modification of normalised difference water index (NDWI) to enhance open water features in remotely sensed imagery*. International Journal of Remote Sensing, 2006. **27**(14): p. 3025-3033.
41. Mann, H.B., *Nonparametric Tests Against Trend*. Econometrica, 1945. **13**(3): p. 245.
42. Meals, D.W., et al., *Statistical Analysis for Monotonic Trends*. US EPA: National Nonpoint Source Monitoring Program: Tech Notes, 2011. **6**.
43. Helsel, D.R. and R.M. Hirsch, *Statistical methods in water resources*. Vol. 49. 1992: Elsevier.