THESIS

TRENDS AND CONTROLS ON LAKE COLOR IN THE HIGH ELEVATION WESTERN UNITED STATES

Submitted By

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ABSTRACT

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Lakes are perceived to be having an increase in algal blooms across the Western United States due to climate change driven and other anthropogenic drivers. Despite this perception, long-term records do not exist for many lakes, so looking at macroscale patterns is challenging. We present and discuss here our results from using a remote sensing dataset, LimnoSat-US. LimnoSat-US contains Landsat imagery from 1984 to 2020. In the intermountain west, our focus study region of Colorado, Wyoming, Idaho, Montana, New Mexico, and Utah, LimnoSat includes 1,200 lakes and over 150,000 summer observations of water color and reflectance. We used LimnoSat-US to examine what controls lake color and what, if any, changes are occurring lake color, which is a strong indicator of whether a lake is prone to algae blooms. A lake's mean depth and annual temperature were the strongest predictors of whether a lake was, on average, blue and clear or green and murky. Despite the perception of increased algae blooms, we found no consistent evidence of lakes "greening" or shifting from mostly oligotrophic, blue, and clear to eutrophic, green, and murky. Instead, the vast majority of our lakes (> 80%) had no trend in lake color. Further, we found that our approach did not capture the dominant controls on whether not a lake was shifting from blue to green or green to blue, highlighting the need for additional work.

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1. Introduction

Throughout the Western United States, high elevation lakes and reservoirs form the basis of a critical water supply network for arid and semi-arid climates downstream (Wheater et al, 2002). Historically, these ecosystems have provided a myriad of services including aesthetic beauty, clean drinking water throughout the year, thriving fisheries, and other services (Messerli et al., 2004). However, climate change poses a direct threat to these lake ecosystems in several ways: altering temperature regimes (Woolway et al., 2020), altering lake ice phenology (Benson et al., 2011), and ecosystem function and biological composition (Oleksy et al., 2021). These slow, or “press”, changes from climate change are coupled with increasing risks posed by short, intense “pulse” disturbances like fires and floods (Hurteau et al., 2014). Together these press and pulse disturbances can interact to alter the ecology of high elevation lakes, potentially causing shifts from oligotrophic (clear water), diatom dominated systems to mesotrophic or eutrophic systems more dominated by algae (Oleksy et al., 2021). This shift could pose a major threat to the ability for these systems to continue to provide their vital services to downstream communities. Further, climate change impacts are likely to impact high elevation systems faster than others, making high elevation lakes sentinels of these kinds of climate induced shifts (Moser et al., 2019, O’Reilly et al., 2009).

Despite the potential threat to these systems changing, there are few studies that examine shifts in lake ecosystems at large spatial scales. There has been focused work on change in a few, pristine high elevation lakes (Moser et al., 2021; Preston et al., 2016). The broad spatial and temporal change that is occurring in these high elevation lakes is significant, as it is part of the ‘Great Acceleration’ of the Anthropocene (Steffen et al., 2015), where they are warming at an alarming rate and are found to have increased algae biomass (Olesky et al., 2017). While there has been recent research looking at continental scale lake change, or regional lake change in the arctic (Kuhn et al., 2021), there has been no such work focused on high elevation lake shifts (Topp, Dugan, et al., 2021; Topp, Stanley, et al., 2021). This could be because there is very little in-situ data at regional scales to be able to interrogate any changes in lake ecosystem functioning (Stanley et al., 2019).

Remote sensing can help address the relative lack of data across the intermountain west by allowing us to look back at imagery collected consistently and systematically across the world. Using Landsat data, we can explore water quality dating back to 1984 (Barnes et al., 2014), by essentially understanding the relationship between lake color and ecosystem function, a long-studied approach to understanding lake ecology (Wang et al., 2015). Analyzing the petabytes of Landsat imagery, they can potentially allow us to address some of the biases that are involved in having little in-situ data at regional scales (Sharma et al., 2015), by means of color analysis. The Forel-Ule system is part of this long-studied approach, dating back to the 1890s, by analyzing color of bodies of water; there is a standard scale of 21 colors that classify gross biological activity and transparency of the water based on what the water looks like (Wernand et al., 2010). Further, the Forel-Ule index can be directly mapped to how humans perceive a lake's color. This analysis is called "Dominant Wavelength Analysis," which uses a combination of the blue, green, and red Landsat bands to estimate the color of a lake to the human eye. This wavelength will tell us a lot about if a lake is clear, oligotrophic, and bluer (wavelengths from 470 to 530 nm) or green, murky, and eutrophic (wavelengths > 530 nm).

While Landsat imagery holds promise for understanding how high elevation lakes are changing, it is not a perfect platform. Specifically for lakes, we want to know are they shifting from clear, oligotrophic systems to turbid, algae-dominated systems, with high chlorophyll a concentration, a correlate of algae biomass. However, while accurate predictions of overall lake clarity are possible at this scale (Topp et al., 2020), predicting chlorophyll a concentration with the full Landsat image stack dating back to 1984 is not always reliable and subject to systematic bias, though progress is being made on newer platforms like Landsat 8 and Sentinel 2 (Olmanson et al, 2008, Timing et al., 2016). Rather than using the imagery to look specifically at chlorophyll a concentration, we can directly use the color of water as a useful indicator of water quality, as color is a strong indicator of total organic carbon (TOC), dissolved organic carbon (DOC) (Ouyang et al., 2006), chlorophyll-a (Cao et al., 2020), colored dissolved organic matter (CDOM) (Griffin et al., 2018), and suspended sediment (Dekker et al., 2001). Furthermore, estimating chlorophyll a concentration is critical when it comes to monitoring water quality, which can be seen via color in a lake; the greener the lake, the higher the chlorophyll a concentration is in the lake (Moses et al., 2009).

Here, we use Landsat imagery, specifically the LimnoSat-US dataset (Topp et al., 2021), to answer two core questions about lake color in the intermountain west – which includes Idaho, Colorado, Montana, Wyoming, Utah, and New Mexico:

1) **What drives patterns of average summer lake color in the intermountain west over the past three decades?**
2) **How are lakes changing color and what drives these changes?**

These questions allow us to begin to understand how climate change and other disturbances are likely to impact lakes now and into the future, and which regions might be most vulnerable to change.

2. **Methods**

In addition to working with Landsat data, we wanted to compare our results to in-situ datasets of water quality in lakes and reservoirs. However, we did not find enough data for our analysis, even after building the largest in-situ dataset of chlorophyll-a and other water quality parameters in Colorado as a test case. As such, we did not analyze this data here, but present some results of where data was available to contrast with the remote sensing data. The in-situ data was obtained from a few different sources. The first major source of data is from Northern Water's water quality data. The data from Northern Water includes data dating back to 1970 for 7 lakes. Most of this data is historic secchi data, primarily for Carter Lake and Horsetooth Reservoir. After contacting Denver Water, through their data request portal, 4,920 data points were obtained that included data dating back to 2000 for Chlorophyll-a, secchi depths, and turbidity, with most of the data being turbidity data. The third source of data is Pueblo Reservoir, which was obtained from the USGS. The data from Pueblo Reservoir includes chlorophyll and secchi data. The in-situ data contained both secchi depth and chlorophyll-*a* data for the locations in Colorado.

The remote sensing data was collected from the LimnoSat-US database (Topp et al., 2020). LimnoSat-US is a robust collection of data that contains data for 56,792 lakes from over 328,000 scenes of remotely sensed imagery. The LimnoSat data extracts USGS Tier 1 surface reflectance values over Landsat 5, Landsat 7, and Landsat 8 sensors dating back to 1984. Ongoing research has shown that the surface reflectance values can be used to estimate inland water quality (Griffin et al., 2018; Kuhn et al., 2019). All the Landsat imagery has been atmospherically corrected, and then adjusted so each satellite had unbiased data (Topp et al., 2020). Reflectance values were extracted from water pixels within 120m of the Chebyshev Center - or the 'deepest' point of a lake, where one can draw the largest circle around water in the lake (Shen et al., 2015). As a second protection to prevent influence from bed and nearshore land pixels, all the lakes looked at are greater than 0.01 km^2; using lakes any smaller than this would make it harder to obtain a pixel in the center of the lake that does not also contain shoreline. Observations were removed if cloud, cloud shadow, snow, or ice were detected using the pixelQA band (Topp et al., 2020). This allowed for each lake to have median values of each band (i.e., blue, green, red, etc.)

from the Landsat imagery, as well as an equation to be used to find the dominant wavelength (Topp et al., 2020). The dominant wavelength was quantified by looking at the human visible spectrum surface reflectance values (red, green, blue), then converted into chromaticity coordinates (Wang et al., 2015). Using the color coordinates, hue angle gets calculated and converted into dominant wavelength by utilizing the International Commission on Illumination look-up tables (Topp et al., 2021).

With LimnoSat-US lake color, we then joined this data to the National Hydrography Dataset and Global Lake Area, Climate, and Population dataset (Meyer et al., 2020). These datasets include additional information that might explain patterns of lake color including modelled lake depth, area, elevation, mean annual temperature, monthly precipitation averages, population data for the lake basin, and other key information (Meyer et al., 2020). Lakes with complete information across all these datasets, and that were above 1000 meters were included in our candidate analysis dataset. This included over 2000 lakes in the intermountain west.

This dataset was further pruned to include only lakes that had at least 3 summer cloud-free images for 30 out of the past 35 years (1985-2020). One important part of looking at the patterns of variability was determining what would be classified as summer months. It has been shown in previous studies that using summertime from June 15 to September 15 (Ouyang et al., 2006; Stanley et al., 2019) works best, showing the best seasonal correlation of water quality parameters across seasons. This final dataset included 1200 lakes in our region (Figure 1).

For the analysis of median summer lake color, we binned lake observations by near decadal periods from 1985-1996, 1997-2008, 2009-2020. For each of these periods, we took a median of the Dominant Wavelength over the full period. This data was then used in a regression tree analysis to determine dominant controls on whether a lake was classified as bluer (wavelengths less than 530 nm) or more green/yellow (wavelength > 530 nm) for each decadal period. Regression tree analysis was performed to identify the different factors that influenced whether the lake's median color was blue or green. Potential predictors included the mean annual air temperature (°C), mean lake depth (m), mean monthly precipitation (mm), elevation (m), latitude, and the area of the lake (km^2). The Classification and Regression Trees (CART) method was used to create the decision trees, and iterated 1000 times with cross-fold validation to determine the optimum tradeoff between model complexity and accuracy. We chose to setup parameters that ensured the model would preference simpler decision trees. The CART method iteratively divides the data into homogeneous groups, based on a threshold in the explanatory variables, while trying to minimize the residual sum of squared error (RSS) amongst the two groups (De'ath et al., 2002; O'Reilly et al., 2015).

For the long-term color trend analyses, we used mean, median, max, and min summer averages of lake color to explore if there were trends in any of these metrics. We used Thiel-Sen's slope estimator to determine the change of color over decades with a P value of 0.05 used to determine if there was significant change. Each lake was analyzed for all four parameters for trend detection and grouped into 5 possible categories: **1) No trend,** when the P value of the Sen's slope was greater than 0.5, all other categories had P values of < 0.05. **2) Blue -> Green**, for lakes that started in the first decade with a DWL value of < 530 nm and a positive slope (going from blue to green/yellow), **3) Green -> Yellow** for lakes with positive slope but were already green (DWL > 530 nm), 4) **Green -> Blue** for lakes with a negative slope value that started out green, and **5) Blue -> Bluer** for lakes that started out blue and got more blue. Sen's slope is a non-parametric test that robustly fits lines to points. It does this by taking the median of the slopes of the lines through the points (Rahman et al., 2016). Sen's slope performs well and is often used in meteorological time series, as well as when there is a gap in data (Yunling et al., 2005).

3. **Results and Discussion**

3.1. **Geography of decadal median lake color**

After trimming our data, the final LimnoSat-US data for the region has more than 150,000 observations for the summer months. This can be seen across 1200 lakes and reservoirs in figure 1, over the past 36 years. When comparing this remotely sensed data to in-situ observations (figure 2), we can see a clear difference in the amount of available data. There are over 15,000 observations of chlorophyll-a for the summer months, despite trying to accumulate as much publicly available data as possible for the state of Colorado. The 15,000 observations of chlorophyll a came from 38 lakes.

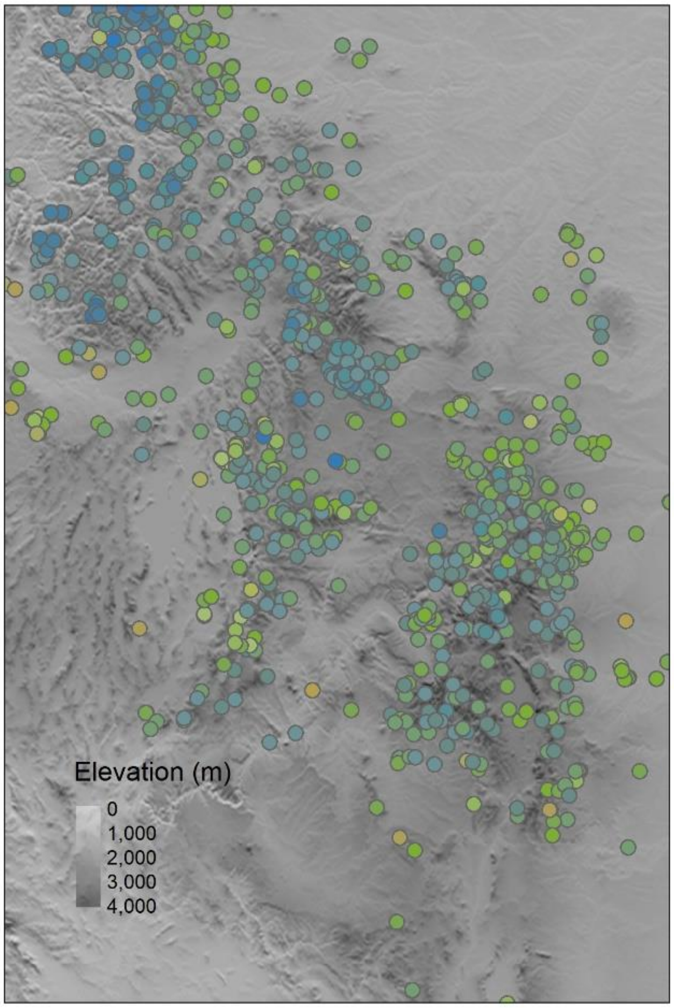

Figure 1 – Map of available LimnoSat-US lakes, where each dot represents a lake, and the color represents the actual median color between 2009-2020 on the Forel-Ule lake color scale.

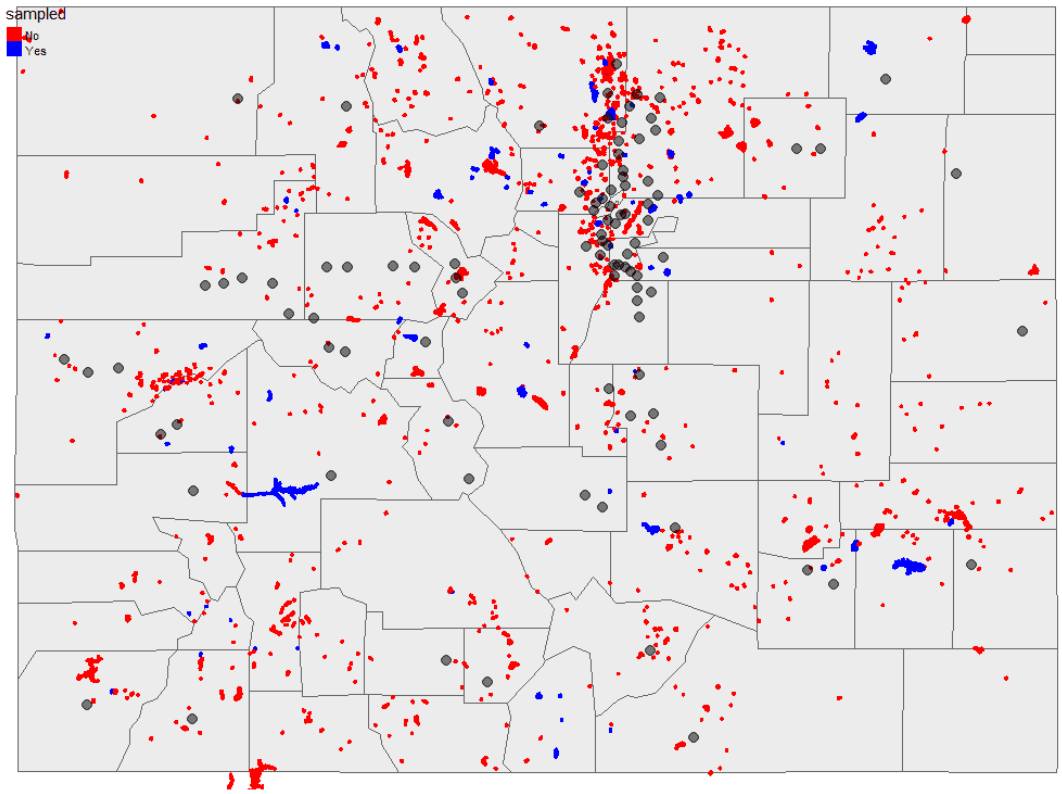

Figure 2 – Map of remote sensing available data vs in-situ sampled lakes.

To look at longer-term averages of lake color, and examine the controls on average lake color, the dataset was divided into 3 decades to look at summertime dominant wavelength, seen in figure 3. This allows us to see the change over time in the dominant wavelength to see the shift in color over decades, whether there was a blue-shift (to lower wavelengths) or green-shift (to higher wavelengths). When looking at the histograms, we can see that they are bimodal; the two maxima wavelengths are in the blue (450-530 nm) and green (530-590 nm). The primary mode is in the blue, around 490 nm, whereas the secondary mode is in green, around 560 nm. There are little observations in between the two, where the black bar – which divides blue and clear lakes from green and murky lakes – is. Comparing across these histograms we can see that there is no dramatic shift in lake color distributions in the past thirty years, showing relative stability in the region.

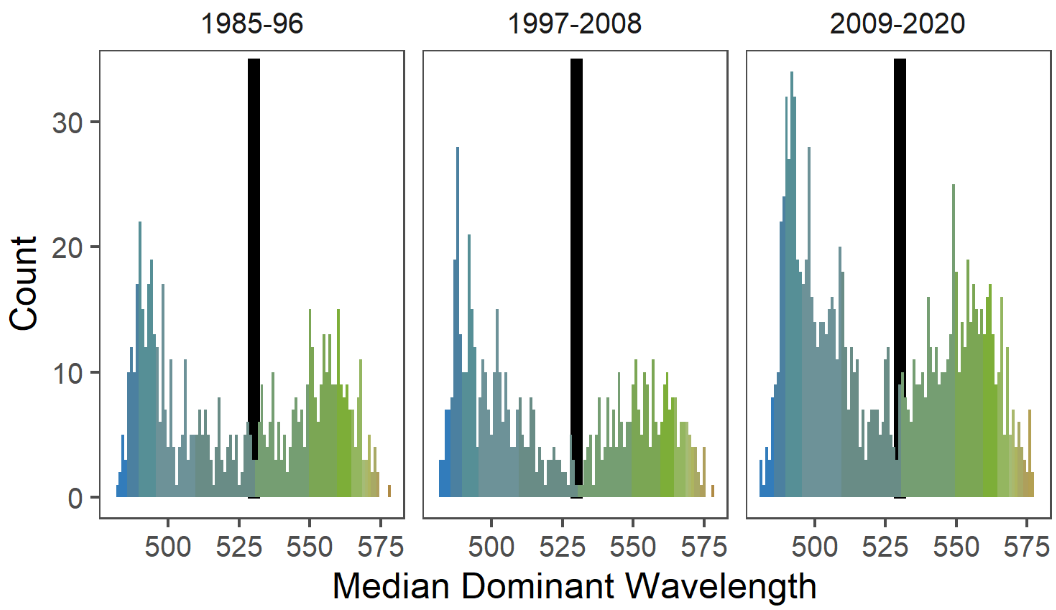

Figure 3 – Median dominant wavelength counts for the arid-west area, across 3 decades. The black bar divides blue/clear lakes on the left from green/murky lakes on the right.

To determine why some colors are green and others are blue, we performed CART (figure 4). By focusing our analysis to only include the most important variables, we find that a lake's mean depth and mean annual air temperature are strong predictors of whether it is green. Not surprisingly, deeper, and cooler lakes that likely have permanent winter ice cover are much more likely to be blue, while warmer, shallower lakes are much more likely to be green. This is particularly important, as it means that the lakes that are freezing, or that the freezes that they do have do not last very long, are more likely to be blue/clear (Hampton et al., 2016). This can also be seen from the length of ice duration (Magnuson et al., 2000) and the air temperatures which dictate the summer stratification timing. Earlier summer stratification causes the surface water to warm faster in larger lakes, whereas in smaller lakes surface temperatures are impacted greater by the air temperature (Toffolon et al., 2014). Critically our decision tree was 78% accurate when assigning blue or green lake color to a set of lakes that were not used in the training algorithm, indicating these controls are robust across the study domain.

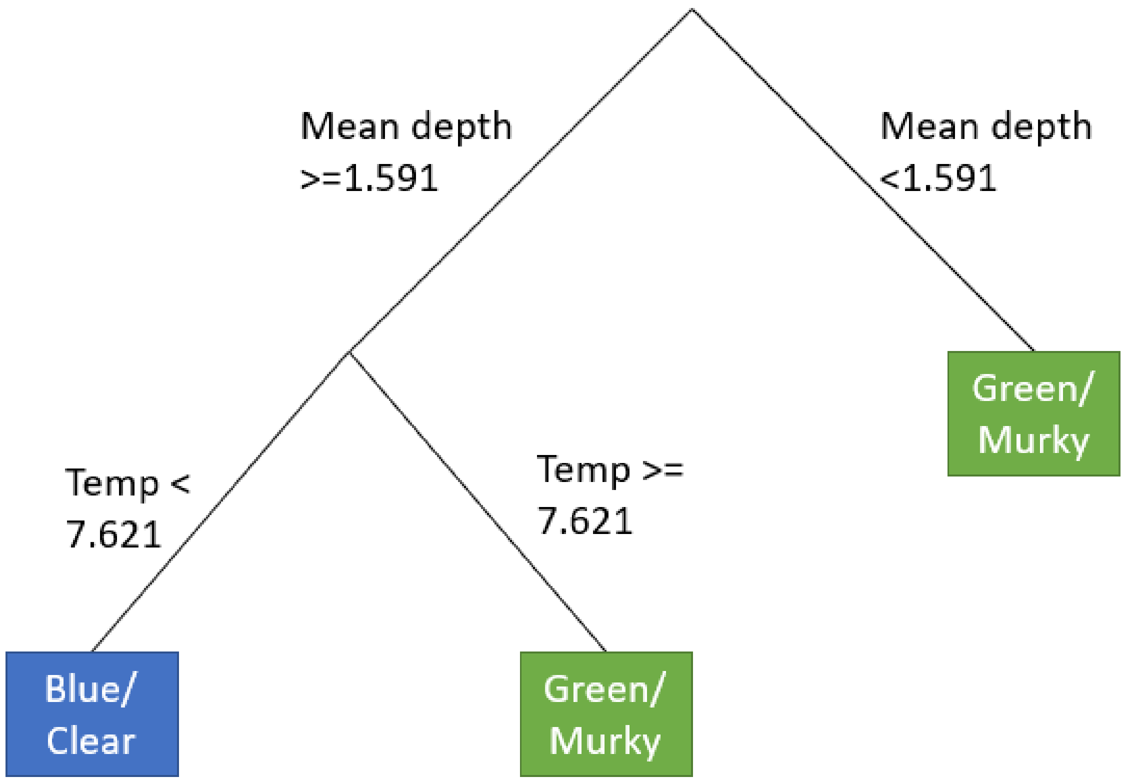

Figure 4 – Decision tree showing that mean depth and mean annual air temperature to determine whether a lake was blue/clear or green/murky.

3.2. **Lake color change**

All lakes were tested for trends in lake color using Thiel Sen's Slope analysis for the mean, median, max, and min of lake summer color. To demonstrate this analysis for lake median color, we randomly selected examples of each possible lake trend and displayed these individual summer lake color observations, their trend, overlaid by all trendlines for lakes in that category (Figure 5). The majority of lakes had no trend across all statistics (min, median, max, mean), with roughly balanced trends in increasing dominant wavelengths and decreasing dominant wavelengths, showing a truly equivocal result (figure 6). While most of the examples show a linear trend, we see in the Green -> Yellow an example of a lake that experienced a dramatic short-term shift in color over only two years. This was part of the Great Salt Lake, where a bridge installation caused a sudden, dramatic shift in a lake from blue to deep green. Our approach does not account for these sudden shifts very well, but they are a strong minority of cases.

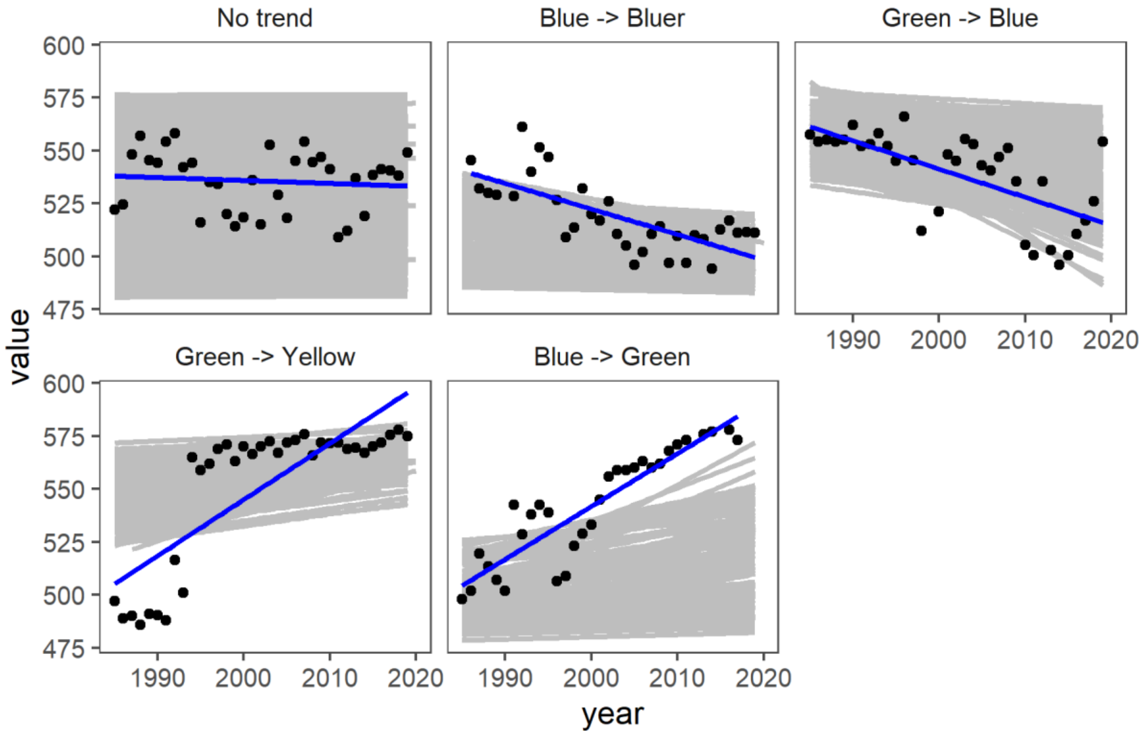

Figure 5 – An example of what the different trends look like.

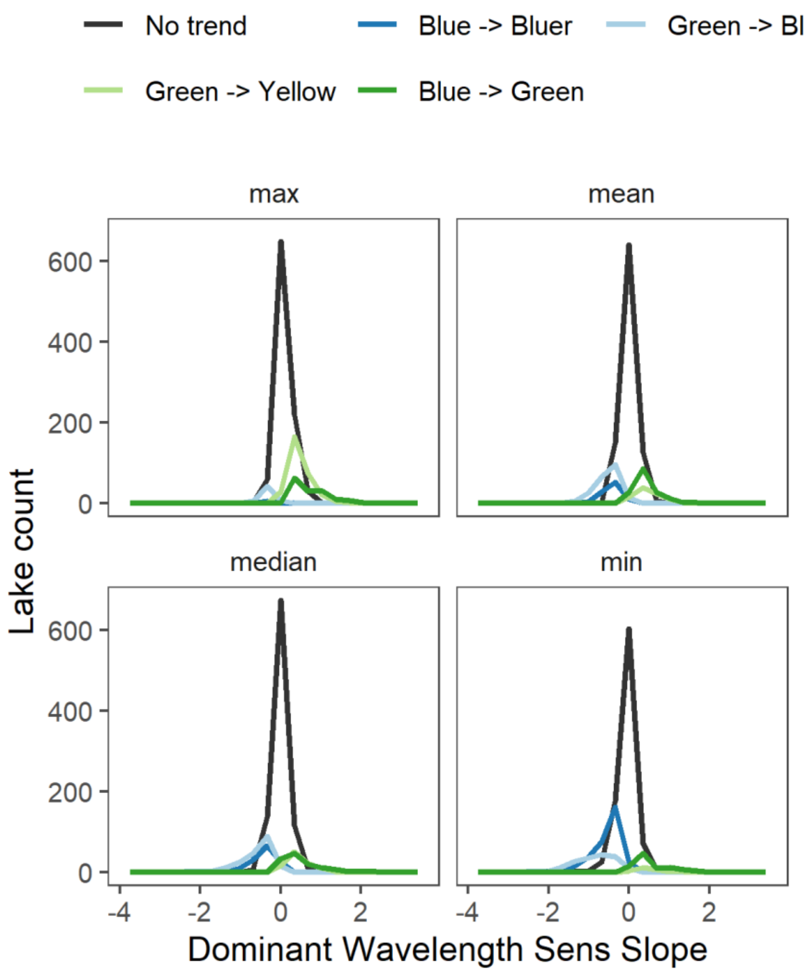

Figure 6 – Sen's slope of the dominant wavelength, showing the max, mean, median, and min of the 5 trend types.

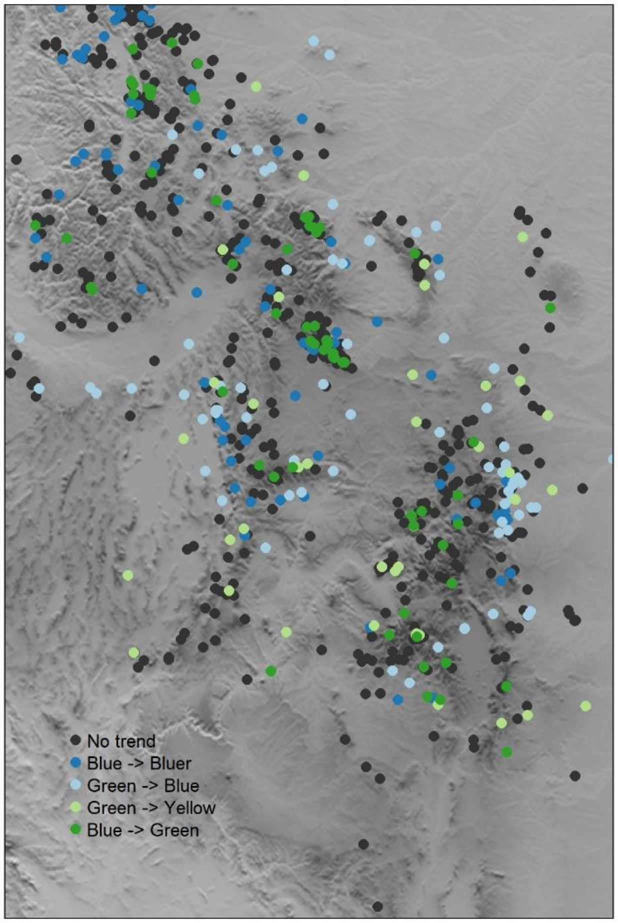

Figure 7 – A map of the lakes and their corresponding trends.

When examining shifts in color at the regional scale (figure 7), we can see that there are some clusters of change, while other areas have lakes very close together experiencing opposite trends. For example, in the Colorado Front Range from Denver to Fort Collins, there is a cluster of lakes going from green to blue or blue to bluer, whereas in the southern section of the Wind River range in central west Wyoming, we see a tight cluster of lakes going from blue to green. Still, the overall trend is that lakes are not changing color and have had consistent ecology for the past 36 years.

3.3. What drives the color change?

A decision tree (figure 8) was also made through the CART method that was aimed at determining what color trend the lakes were experiencing. This tree shows again that depth, and temperature are important drivers of lake trends, but that precipitation and elevation also play an important role. We tested the validity of this this tree by making predictions of trend category for lakes that had not been used in the training of the CART algorithm. In this validation, we found that our relatively simple CART tree had almost no ability to determine which lakes were likely to be experiencing any color shift, it could only somewhat accurately predict which lakes would have no trend (figure 9). As such, while the tree is useful to look at what characteristics might make a lake more prone to change, it cannot help us predict what lakes are changing. The tree is sensitive, especially to spatial autocorrelation (Sinha et al., 2019), which we did not account for in our analysis, but we know is present in the data.

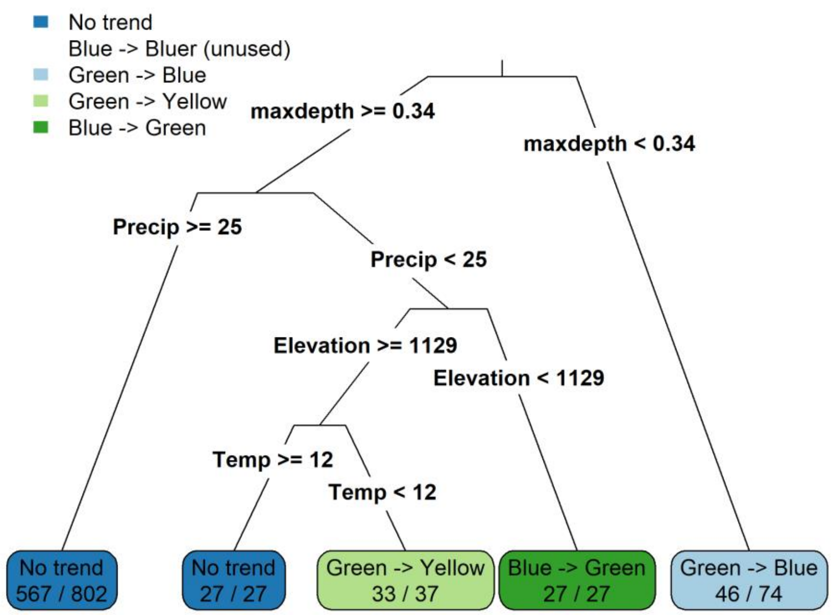

Figure 8 – Decision tree to determine the color shift of the different lakes.

Figure 9 – Confusion matrix that shows the predictive outcome of the tree vs the true value of the lake.

4. Conclusions

Most current research on summer lake color is typically on lakes that have a rich history of being sampled – likely because they are a significant water supply reservoir or lake (Stanley et al., 2019). Cross-landscape studies are uncommon, which leaves us with small groupings of studies allowing us to understand mostly fine-scale controls on lake ecology, like at the Great Lakes (Soranno et al., 2014). This study allows for a larger-scale analysis looking at color across a landscape that otherwise would not have the in-situ data required for understanding drivers of change. From the analysis, we found that a large number of lakes have not experienced a shift in color over the past 36 years, as well as a good number of increasing lakes in greenness and roughly equal numbers experiencing a decrease in greenness, contrary to the perception that lakes are experiencing more algal blooms (and thus more chlorophyll a and greenness). This is happening despite well documented studies that high elevation lakes can shift their ecological community to more pelagic, algae dominated (Oleksy et al., 2020) and that most of these lakes are experiencing warming over the same time period of our study.

Our dataset is an imperfect tool for detecting ecological changes in lakes, where any changes that are not represented in a lake's color will go undetected. This could create issues where algae blooms really are present, but they are short and intense and are not visible to Landsat's roughly 8- or 16-day return sampling interval. Additionally, we constrained our analysis to the summer months, and it is possible that there are non-summer dynamics that have helped create the perception of lake algae blooms. Still, remote sensing allowed us to determine that most lakes are not changing color, blue lakes are cooler and deeper, and shallower, smaller, warmer lakes are more prone to being green and to shifting from blue to green. Additional work in this area should include a focus on other potential drivers of lake change like land cover shifts, population density, fire extent, and other pulse and press disturbances that could be altering lake color.

These critically important high-elevation lakes may not be experiencing obvious trends in lake color yet, but they are likely going to be impacted by increasing climate change effects of changing precipitation and temperature (Oleksy et al., 2020), as found in our simple decision tree that indicated temperature as a dominant control of overall lake color.

BIBLIOGRAPHY

Adrian, Rita, Catherine M. O'Reilly, Horacio Zagarese, Stephen B. Baines, Dag O. Hessen, Wendel Keller, David M. Livingstone, et al. "Lakes as Sentinels of Climate Change." Limnology and Oceanography 54, no. 6part2 (November 2009): 2283–97. https://doi.org/10.4319/lo.2009.54.6_part_2.2283.

Atta-ur-Rahman, and Muhammad Dawood. "Spatio-Statistical Analysis of Temperature Fluctuation Using Mann–Kendall and Sen's Slope Approach." Climate Dynamics 48, no. 3–4 (February 2017): 783–97. https://doi.org/10.1007/s00382-016-3110-y.

Benson, Barbara J., John J. Magnuson, Olaf P. Jensen, Virginia M. Card, Glenn Hodgkins, Johanna Korhonen, David M. Livingstone, Kenton M. Stewart, Gesa A. Weyhenmeyer, and Nick G. Granin. "Extreme Events, Trends, and Variability in Northern Hemisphere Lake-Ice Phenology (1855–2005)." Climatic Change 112, no. 2 (May 2012): 299–323. https://doi.org/10.1007/s10584-011-0212-8.

Bukata, R. P., J. E. Bruton, J. H. Jerome, S. C. Jain, and H. H. Zwick. "Optical Water Quality Model of Lake Ontario 2: Determination of Chlorophyll a and Suspended Mineral Concentrations of Natural Waters from Submersible and Low Altitude Optical Sensors." Applied Optics 20, no. 9 (May 1, 1981): 1704. https://doi.org/10.1364/AO.20.001704.

De'ath, Glenn, and Katharina E. Fabricius. "CLASSIFICATION AND REGRESSION TREES: A POWERFUL YET SIMPLE TECHNIQUE FOR ECOLOGICAL DATA ANALYSIS." Ecology 81, no. 11 (November 2000): 3178–92. https://doi.org/10.1890/0012-9658(2000)081[3178:CARTAP]2.0.CO;2.

Dekker, A G, R J Vos, and S W M Peters. "Comparison of Remote Sensing Data, Model Results and in Situ Data for Total Suspended Matter ŽTSM/ in the Southern Frisian Lakes," 2001, 18.

Griffin, C.G., J.W. McClelland, K.E. Frey, G. Fiske, and R.M. Holmes. "Quantifying CDOM and DOC in Major Arctic Rivers during Ice-Free Conditions Using Landsat TM and ETM+ Data." Remote Sensing of Environment 209 (May 2018): 395–409.

https://doi.org/10.1016/j.rse.2018.02.060.

Hampton, Stephanie E., Aaron W. E. Galloway, Stephen M. Powers, Ted Ozersky, Kara H. Woo, Ryan D. Batt, Stephanie G. Labou, et al. "Ecology under Lake Ice." Edited by James Grover. Ecology Letters 20, no. 1 (January 2017): 98–111. https://doi.org/10.1111/ele.12699.

Hollister, J. W., D. Q. Kellogg, B. J. Kreakie, S. D. Shivers, W. B. Milstead, E. M. Herron, L. T. Green, and A. J. Gold. "Analyzing Long-term Water Quality of Lakes in Rhode Island and the Northeastern United States with an Anomaly Approach." Ecosphere 12, no. 6 (June 2021). https://doi.org/10.1002/ecs2.3555.

Hollister, Jeffrey W., W. Bryan Milstead, and Betty J. Kreakie. "Modeling Lake Trophic State: A Random Forest Approach." Edited by D. P. C. Peters. Ecosphere 7, no. 3 (March 2016). https://doi.org/10.1002/ecs2.1321.

Hurteau, Matthew D., John B. Bradford, Peter Z. Fulé, Alan H. Taylor, and Katherine L. Martin. "Climate Change, Fire Management, and Ecological Services in the Southwestern US." Forest Ecology and Management 327 (September 2014): 280–89. https://doi.org/10.1016/j.foreco.2013.08.007.

Kuhn, Catherine, and David Butman. "Declining Greenness in Arctic-Boreal Lakes." Proceedings of the National Academy of Sciences 118, no. 15 (April 13, 2021): e2021219118. https://doi.org/10.1073/pnas.2021219118.

Magnuson, J. J. "Historical Trends in Lake and River Ice Cover in the Northern Hemisphere." Science 289, no. 5485 (September 8, 2000): 1743–46. https://doi.org/10.1126/science.289.5485.1743.

Messerli, Bruno, Daniel Viviroli, and Rolf Weingartner. "Mountains of the World: Vulnerable Water Towers for the 21st Century." AMBIO: A Journal of the Human Environment 33, no. sp13 (November 13, 2004): 29. https://doi.org/10.1007/0044-7447-33.sp13.29.

Meyer, Michael F., Stephanie G. Labou, Alli N. Cramer, Matthew R. Brousil, and Bradley T. Luff. "The Global Lake Area, Climate, and Population Dataset." Scientific Data 7, no. 1 (December 2020): 174. https://doi.org/10.1038/s41597-020-0517-4.

Moser, K.A., J.S. Baron, J. Brahney, I.A. Oleksy, J.E. Saros, E.J. Hundey, S. Sadro, et al. "Mountain Lakes: Eyes on Global Environmental Change." Global and Planetary Change 178

(July 2019): 77–95. https://doi.org/10.1016/j.gloplacha.2019.04.001.

Moses, W J, A A Gitelson, S Berdnikov, and V Povazhnyy. “Estimation of Chlorophyll- a Concentration in Case II Waters Using MODIS and MERIS Data—Successes and Challenges.” Environmental Research Letters 4, no. 4 (October 2009): 045005. https://doi.org/10.1088/1748-9326/4/4/045005.

Oleksy, Isabella A., Jill S. Baron, and Whitney S. Beck. “Nutrients and Warming Alter Mountain Lake Benthic Algal Structure and Function.” Freshwater Science 40, no. 1 (March 1, 2021): 88–102. https://doi.org/10.1086/713068.

Preston, Daniel L., Nel Caine, Diane M. McKnight, Mark W. Williams, Katherina Hell, Matthew P. Miller, Sarah J. Hart, and Pieter T. J. Johnson. “Climate Regulates Alpine Lake Ice Cover Phenology and Aquatic Ecosystem Structure.” Geophysical Research Letters 43, no. 10 (May 28, 2016): 5353–60. https://doi.org/10.1002/2016GL069036.

Sharma, Sapna, Derek K Gray, Jordan S Read, Catherine M O’Reilly, Philipp Schneider, Anam Qudrat, Corinna Gries, et al. “A Global Database of Lake Surface Temperatures Collected by in Situ and Satellite Methods from 1985–2009.” Scientific Data 2, no. 1 (December 2015): 150008. https://doi.org/10.1038/sdata.2015.8.

Sinha, Parmanand, Andrea E. Gaughan, Forrest R. Stevens, Jeremiah J. Nieves, Alessandro Sorichetta, and Andrew J. Tatem. “Assessing the Spatial Sensitivity of a Random Forest Model: Application in Gridded Population Modeling.” Computers, Environment and Urban Systems 75 (May 2019): 132–45. https://doi.org/10.1016/j.compenvurbsys.2019.01.006.

Stanley, Emily H., Sarah M. Collins, Noah R. Lottig, Samantha K. Oliver, Katherine E. Webster, Kendra S. Cheruvelil, and Patricia A. Soranno. “Biases in Lake Water Quality Sampling and Implications for Macroscale Research.” Limnology and Oceanography 64, no. 4 (July 2019): 1572–85. https://doi.org/10.1002/lno.11136.

“TD_055_2002.Pdf,” n.d.

Toffolon, Marco, Sebastiano Piccolroaz, Bruno Majone, Anna-Maria Soja, Frank Peeters, Martin Schmid, and Alfred Wüest. “Prediction of Surface Temperature in Lakes with Different Morphology Using Air Temperature.” Limnology and Oceanography 59, no. 6 (November 2014): 2185–2202. https://doi.org/10.4319/lo.2014.59.6.2185.

Toming, Kaire, Tiit Kutser, Alo Laas, Margot Sepp, Birgot Paavel, and Tiina Nõges. “First Experiences in Mapping Lake Water Quality Parameters with Sentinel-2 MSI Imagery.” Remote Sensing 8, no. 8 (August 5, 2016): 640. https://doi.org/10.3390/rs8080640.

Topp, Simon N., Tamlin M. Pavelsky, Hilary A. Dugan, Xiao Yang, John Gardner, and Matthew R.V. Ross. “Shifting Patterns of Summer Lake Color Phenology in Over 26,000 US Lakes.” Water Resources Research 57, no. 5 (May 2021). https://doi.org/10.1029/2020WR029123.

Topp, Simon N., Tamlin M. Pavelsky, Daniel Jensen, Marc Simard, and Matthew R. V. Ross. “Research Trends in the Use of Remote Sensing for Inland Water Quality Science: Moving Towards Multidisciplinary Applications.” Water 12, no. 1 (January 7, 2020): 169. https://doi.org/10.3390/w12010169.

Topp, Simon N, Tamlin M Pavelsky, Emily H Stanley, Xiao Yang, Claire G Griffin, and Matthew R V Ross. “Multi-Decadal Improvement in US Lake Water Clarity.” Environmental Research Letters 16, no. 5 (May 1, 2021): 055025. https://doi.org/10.1088/1748-9326/abf002.

Wang, Shenglei, Junsheng Li, Qian Shen, Bing Zhang, Fangfang Zhang, and Zhaoyi Lu. “MODIS-Based Radiometric Color Extraction and Classification of Inland Water With the Forel-Ule Scale: A Case Study of Lake Taihu.” IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing 8, no. 2 (February 2015): 907–18. https://doi.org/10.1109/JSTARS.2014.2360564.

Wernand, M. R., and H. J. van der Woerd. “Spectral Analysis of the Forel-Ule Ocean Colour Comparator Scale.” Journal of the European Optical Society: Rapid Publications 5 (April 27, 2010): 10014s. https://doi.org/10.2971/jeos.2010.10014s.