Title: Heterogenous controls on lake color and trends across the high-elevation U.S. Rocky Mountain region

Authors: Isabella Oleksy[a*], Sarah Collins[a], Samuel J. Sillen[a], Simon Topp[b], Miles Austin[c], Edward K. Hall[c], Catherine M. O'Reilly[d], Xiao Yang[b], Matthew R.V. Ross[c]

Affiliations:

[*] Corresponding author; bellaoleksy@gmail.com

[a] Department of Zoology and Physiology, University of Wyoming, Laramie, WY, USA

[b] Department of Geological Sciences, University of North Carolina at Chapel Hill, Chapel Hill, NC, USA

[c] Department of Ecosystem Science and Sustainability, Colorado State University, Fort Collins, CO, USA

[d] Department of Geography, Geology, and the Environment, Illinois State University, Normal, IL, USA

Running head: Lake color trends Rockies

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Abstract

Global change may contribute to ecological changes in high-elevation lakes and reservoirs, but a lack of data makes it difficult to evaluate spatiotemporal patterns. Remote sensing imagery can provide more complete records to evaluate whether consistent changes across a broad geographic region are occurring. We used Landsat surface reflectance data to evaluate spatial patterns of contemporary lake color (2010-2020) in 940 lakes in the U.S. Rocky Mountains, a historically understudied area for lake water quality. Intuitively, we found that most of the lakes in the region are blue (66%) and were found in steep-sided watersheds (>22.5º) or alternatively were relatively deep (>4.5m) with mean annual air temperature (MAAT) <4.5ºC. Most green/brown lakes were found in relatively shallow sloped watersheds with MAAT ≥4.5ºC. We extended the analysis of contemporary lake color to evaluate changes in color from 1984-2020 for a subset of lakes with the most complete time series (n=527). We found limited evidence of lakes shifting from blue to green states, but rather, 55% of the lakes had no trend in lake color. Surprisingly, where lake color was changing, 32% of lakes were trending toward bluer wavelengths, and only 13% shifted toward greener wavelengths. Lakes and reservoirs with the most substantial shifts toward blue wavelengths tended to be in urbanized, human population centers at relatively lower elevations. In contrast, lakes that shifted to greener wavelengths did not relate clearly to any lake or landscape features that we evaluated, though declining winter precipitation and warming summer and fall temperatures may play a role in some systems. Collectively, these results suggest that the interactions between local landscape factors and broader climatic changes can result in heterogeneous, context-dependent changes in lake color.

Introduction

High-elevation lakes and reservoirs form the basis of a critical water supply network for arid and semi-arid cities and communities downstream. However, climate change threatens these ecosystems via altered temperature and precipitation regimes (Christianson et al., 2020; Maberly et al., 2020), lake ice phenology (Benson et al., 2012; Preston et al., 2016), lake temperature (Christianson et al., 2019; Sadro et al., 2018; Smits et al., 2020) and, in turn, ecosystem function and biological composition. In addition to climate change, increasing nutrient loading presents an additional steady change that can lead to increased algal production (Moser et al., 2019; Oleksy et al., 2021).

Despite these potential threats to high-elevation lakes, examining shifts in freshwater ecosystems at large spatial scales is challenging because of inadequate coverage and a strong bias of analyses towards a few well-monitored lakes (Stanley et al., 2019). Physiochemical changes (e.g., ice-cover duration, water chemistry, surface temperature) in a number of pristine high-elevation lakes suggests that these shifts are significant (Moser et al., 2019; Preston et al., 2016). Summer warming in combination with nitrogen deposition is leading to algal assemblage shifts and increasing productivity in lakes along the Colorado Front Range (Oleksy et al., 2020). In addition, snowpack and summer weather conditions are strong controls on water chemistry and algal biomass for mountain lakes (Oleksy et al., 2020; Preston et al., 2016; Sadro et al., 2018). While there has been recent research examining regional to continental scale changes in lake nutrients (Oliver et al., 2017; Stoddard et al., 2016), water clarity (Topp et al., 2021), lake color (Kuhn and Butman, 2021), and algal blooms (Wilkinson et al., 2021) there have been no regional studies, to our knowledge, on high-elevation lake shifts likely due to a lack of *in situ* water quality monitoring data (Read et al., 2017).

While remote sensing can be used to directly estimate water quality parameters (Topp et al., 2020), lake water color is relatively easy to infer from satellite and is less prone to prediction errors (Giardino et al., 2014). Color is also an intuitive and integrative metric that can serve as an indicator of water quality parameters, including colored dissolved organic matter, which can be used to infer estimates of total organic carbon, dissolved organic carbon (Ouyang et al., 2006), chlorophyll-a (proxy for algal productivity; Cao et al., 2020), and suspended sediment (Dekker et al., 2001).

Here we used satellite-derived lake color to address three core objectives to better understand lake color in the U.S. Rocky Mountains:

1. We evaluated the contemporary spatial distribution of average summer lake color.
2. We quantified how lake color has changed in the region since the beginning of the Landsat record (1984).

3. We examined which lake, landscape, and climatological features of lakes relate to spatial patterns and temporal trends in lake color.

Through these three objectives we aimed to understand the current patterns of lake color across the U.S. Rocky Mountain region and to assess how climate change and other disturbances might be changing or will change color, and therefore, lake ecology and related ecosystem characteristics.

Methods

Lake color

We used remote sensing data from the LimnoSat-US database (Topp et al., 2020), a robust collection of Landsat surface reflectance data for 56,792 U.S. lakes. The LimnoSat-US data extracts USGS Tier 1 surface reflectance values over Landsat 5, Landsat 7, and Landsat 8 sensors dating back to 1984 from the deepest point of lakes, or the point furthest from any shoreline. All the Landsat imagery has been atmospherically corrected, and then adjusted so each satellite had unbiased data across time and between satellites (Topp et al., 2020). We limited the analysis to high elevation lakes in the Rocky Mountain Region, which we define as the parts of Idaho, Colorado, Montana, Wyoming, Utah, and New Mexico above 1400m. This captures many mountain lakes in the region as well as high-elevation plains lakes and reservoirs. We examined spatiotemporal patterns in the color of the lake, called the Dominant Wavelength (DWL), which maps directly to the Forel-Ule scale, a water transparency classification scale (Wernand and Van der Woerd, 2010). 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 and Van der Woerd, 2010). Further, the Forel-Ule index can be directly mapped to how humans perceive a lake's color. Dominant wavelength is quantified by looking at the human visible spectrum surface reflectance values (red, green, blue) and then converted into chromaticity coordinates (Wang et al., 2015). For both color-measuring approaches, blue lakes (DWL<530nm) are generally considered oligotrophic, while change in color from blue to green wavelengths generally corresponds to shifts in trophic state from mesotrophic to eutrophic (DWL>530nm). Color changes from green toward brown wavelengths can indicate either a dystrophic system or a eutrophic lake with high suspended sediment in the water column (DWL>575nm).

Classification of spatial patterns

To understand broad-scale spatial patterns, we examined the median contemporary (2010-2020) lake color across the U.S. Rocky Mountains. We included data from the summer period (July 1-September 15) to minimize seasonal variation and the impact of snow and ice cover, which can persist into June for some of the highest elevation lakes. We joined the LimnoSat-US lake color data to the National Hydrography Dataset (U.S. Geologic Survey, 2021), the Global Lake Area, Climate, and Population dataset (Smith et al., 2021), watershed-level metrics from the LakeCat database (Hill et al., 2018), LAGOS-US NETWORKS (King et al., 2021) and LAGOS-US Reservoir (Polus et al., 2021). We used information about the lake, landscape, lake type (natural lake or reservoir), and connectivity features from these datasets to explain lake color spatial patterns in lakes that spanned a broad range of environmental contexts (Table 1).

We divided the population of lakes into two categories: blue/clear (DWL<530 nm; n=620) or green/turbid (DWL>530 nm; n=320; Figure 2A). To address our first research objective, we used a Classification and Regression Tree (CART; Therneau and Atkinson, 1997) to determine which environmental characteristics explained variation in lake color across the region using the *rpart* package (Therneau and Atkinson, 2019). The training dataset included 80% of the total population (n=765). We calculated the global model accuracy by predicting lake color groupings for the out-of-sample lakes and assessed model performance with a confusion matrix. We visualized the results with the *cvms* (Olsen and Zachariae, 2021) and *ggparty* (Borkovec and Madin, 2019) R packages for the confusion matrix and decision trees, respectively. All analyses and data visualizations were done in R version 4.0.5 (R Core Team, 2021).

Trend analysis

For the trend analysis, we built a separate dataset that included only lakes that had at least 3 cloud-free summer images for a minimum of 30 consecutive years between 1984-2020 for a total of 527 lakes in the analysis. This accounts for approximately a quarter of all lakes in this region that are greater than 10 ha in area and over 1400m in elevation (Figure S1). We calculated the non-parametric Theil-Sen's slope for each lake time series of median summer color using the *trend* package (Pohlert, 2020). We used the Mann-Kendall z-score and compared the p-value from that z-score to $\alpha = 0.05$. We categorized each lake into one of five possible trend categories:

1) No trend when the p-value of the Sen's slope was greater than 0.05. All other categories had p-values of <0.05;

2) Blue->Greener, for lakes that started blue during the first half of the record (median DWL <530 nm; 1984-2005) and had a positive slope;

3) Intensifying Green/brown for lakes that started green prior to 2005 (median DWL >530 nm) and had a positive slope;

4) **Green->Bluer** for lakes that started green (median DWL >530 nm between 1984-2005) and had a negative slope; and

5) Intensifying Blue for lakes that started blue prior to 2005 (DWL <530 nm) and had a negative slope.

For lakes in the Blue->Greener and Green->Bluer categories, we assessed whether the median lake color in the later part of the record indicated a modal shift in color from predominantly blue to predominantly green/brown, or vice versa, consistent with the spatial color categorization.

We conducted a Random Forest analysis to explore the drivers of color trends (Breiman, 2001). Here, we grouped together all lakes with positive trends (Intensifying Green/Yellow and Blue->Greener) and negative trends (Intensifying Blue and Green->Bluer) into composite categories for a total of three trend categories (Negative, No Trend, Positive). Predictors included all those considered in the spatial CART described above (Table 1) as well as changes in seasonal precipitation, temperature, and human population size. We used the *prism* package (version 0.2.0) to download the daily estimate of temperature and precipitation from the Oregon Parameter-elevation Relationships on Independent Slopes Model (PRISM) project (Hart and Bell, 2015). For each lake-year, we calculated the mean winter (December-February), spring (March-May), summer (June-August), and fall (September-November) temperature and precipitation. Then, we calculated the Sen's slope of temperature and precipitation for each lake and season from 1984-2020.

We built the random forest models using the rand_forest function in the *parsnip* package using the "ranger" engine (Kuhn and Vaughan, 2021a; Wright and Ziegler, 2017). We randomly chose 60% of the data as our training data set and 40% as our test dataset which ensured that at least 25% of the observations in each trend category were set aside for validation. We tuned the two hyperparameters using ten-fold cross-validation. The optimum number of predictors at each node (*mtry* = 4) and the minimum n to split at any node (*min_n* = 3) for the final model was selected according to the best Receiver Operating Characteristic curve and overall classification accuracy using the *yardstick* package (Kuhn and Vaughan, 2021b). The final random forest model consisted of 1000 trees and was evaluated on the validation data. We present the top 10 predictors based on Variable Importance (VI), computer as the total decrease in node impurity averaged over all trees.

Results

Spatial patterns

Our dataset included 940 lakes above 1400m across the six-state Rocky Mountain region (Figure 1). Between 2010-2020, 66% of the lakes were predominantly blue (n=620) while 34% of the lakes were predominantly green/brown (n=320; Figure S2). The CART analysis revealed that watershed slope, mean annual air temperature (MAAT), and maximum lake depth were important determinants of lake color (Figure 2C). Most green/brown lakes were found in relatively shallow sloped watersheds with MAAT ≥4.5ºC. Lakes situated in watersheds with slope angles ≥22.5º were most likely to be classified as blue lakes. Similarly, another set of blue lakes were common in less steep watersheds with MAAT ≤4.5ºC with maximum depth ≥4.5 meters while shallower lakes in those areas were more likely to be green/brown. Watershed slope is negatively correlated with MAAT (r=-0.50) and other factors such as lake elevation that likely influence spatial patterns of lake color (Figure S3). Overall, the CART model was able to correctly classify 84% of blue lakes and 68% of green/brown lakes in the test dataset (Figure 2B).

Cross-lake color trends

In the U.S. Rocky Mountains, we detected no trends in lake color between 1984-2020 in 55% of lakes (n=290, Figure 3). However, 32% of lakes were trending bluer (n=166) and reservoirs showed the largest improvements in water quality. Specifically, 71% of the lakes that trended bluer were reservoirs (n=30), and 75% of the lakes that were intensifying blue were reservoirs (n=30). Most of the lakes trending from Green->Bluer were in Colorado (71% or n=72; Figure 4), including many Colorado reservoirs that switched from Green/brown to blue/clear (n=14, Table S1). Median lake color shifted toward greener wavelengths in 13% of the population of lakes (n=71), with 34 lakes in the Intensifying Green/brown category and 37 lakes in the Blue->Greener category. Of the Blue->Greener lakes, six of them crossed the 530nm threshold consistently in recent years such that they were classified as Green/brown in the spatial analysis.

Although our Random Forest model poorly predicted lake greening (Figure S4), a combination of static variables and climatic trends partially explained some trends in lake color (Figure 5). The variables with highest importance included total human population in the lake-watershed (Variable Importance=6.07), lake elevation (VI=5.91), changes in winter precipitation (VI=5.58), urban landcover

(VI=4.4), and changes of spring temperature (VI=4.25). The majority of the lakes that were Intensifying Blue or trending Green->Bluer were located in relatively urbanized watersheds with some of the highest human population densities in the region (Figure 5A,D). These lakes also tended to be located at lower elevations relative to lakes not experiencing color shifts or lakes that were greening (Figure 5B). Both greening and blueing lakes were associated with decreases in winter precipitation between 1984-2020 compared to lakes with no trend (Figure 5C). Furthermore, blueing lakes tended to be in areas where spring air temperatures were cooling slightly relative to greening lakes or lakes without color changes (Figure 5E), though notably for both the climatic variables only a small subset of the trends were statistically significant (Figure S5, Table S2).

Overall, the most widespread climatic trends in the region were increasing summer and fall temperatures (Table S2). Although increasing fall temperatures were widespread in this region, there were no differences among color trend groups (ANOVA $F_{2,328}=2.55$, $p=0.08$). However, absolute rates of summer warming varied among color groups (Kruskal–Wallis H-test, $p<0.001$). Specifically, since 1984. summer temperatures increased on average 0.23°C more in lakes with no change in color compared to lakes that were trending blue (95% CI: 0.06-0.4°C). Further, rates of summer warming were 0.34°C higher in the greening lakes compared to the blueing lakes (95% CI: 0.11-0.57°C; Figure S5). For lakes that shifted from Blue->Greener, nearly every lake experienced substantial summer warming (Table S2). Precipitation shifts were highly variable, and most lakes did not experience substantial shifts in PRISM-estimated monthly precipitation (Table S2).

Discussion

Our analysis showed that most lakes (55%) included in this study showed no substantial change in lake color between 1984 and 2020. This is consistent with both remote sensing and field studies of regional lake water quality trends in arctic (Kuhn and Butman, 2021) and temperate regions (Oliver et al., 2017; Paltsev and Creed, 2021) that showed a minority of study lakes to be exhibiting changes in lake color. For lakes in the Rocky Mountain region that changed over the past 36 years, most trended bluer (70%), suggesting an overall improvement in summer water quality. While there is a growing concern of widespread declines in water quality, our results build on recent studies that show regional improvements in water quality and a more nuanced understanding of changes in lakes occurring across large spatial scales (Topp et al., 2021; Wilkinson et al., 2021).

Spatial patterns

Our study revealed several putative controls on spatial patterns in lake color in the U.S. Rocky Mountains. Many blue lakes were in steep, high-elevation watersheds, with little vegetative cover and had colder mean annual air temperature than green/brown lakes (Figure S6). Together, these factors likely result in limited terrestrial nutrient subsidies and thus lower productivity and clearer waters (Leavitt et al., 2009; Likens and Bormann, 1974). Heterogeneity in additional factors among these high elevation lakes such as lake morphometry and watershed area may also modify this relationship. For example, some green/brown lakes occurred in cold areas (MAAT<4.5ºC) if they were shallow (<2.5m average depth), particularly if they had larger watersheds (>12.5km^2). This is expected since small, shallow lakes tend to be more productive than deep lakes (Duarte and Kalff, 1989; Genkai-Kato and Carpenter, 2005; Richardson et al., 2022). Conversely, in some shallow lakes, the color that satellites detect may be capturing benthic algal growth, which can make up a majority of the lake productivity in systems where photic zone extends to the benthos (Lõugas et al., 2020). Overall, these spatial patterns are consistent with studies describing continental scale patterns of lake trophic status and water quality, which indicate that high-elevation western mountain ecoregions are generally oligotrophic, with higher prevalence of green, turbid, or eutrophic lakes in the high plains and agricultural ecoregions (Hill et al., 2018; Hollister et al., 2016; Peck et al., 2020).

Controls on cross-lake color trends

Lakes and reservoirs shifting toward bluer wavelengths represented 32% of all sites and frequently occurred in developed, relatively lower elevation areas. Reservoir management in the Western U.S. typically employs a variety of approaches (e.g., hypolimnetic oxygenation, diversifying water supplies) to maintain water resources under increasing climate variability (Beutel and Horne, 1999; Page and Dilling, 2020; Ray, 2003) and these practices may be a driver of the water quality improvements we observed. However, these apparent changes in water color that may be attributed to local management actions were difficult to capture in our statistical analyses because we lacked broad-scale databases that summarize management efforts for this region. For instance, increases in reservoir storage, resulting in greater volume of water, may result in an apparent blueing of waters, but our study lacks data on changing lake surface area or volume. In addition, managed movement of water across the landscape could further obscure relationships between watershed characteristics and local water quality trends. For example, we observed clusters of reservoirs with blueing trends in the heavily populated Colorado Front Range, but trans-basin water diversions are common in that area (Wiener et al., 2008) making it even more difficult to link management practices to changing water color. Our results suggest that management practices over the same period may have led to improving water quality in ecosystems that are often used for drinking water.

A relatively small proportion of lakes (13%) exhibited characteristics indicative of decreasing water quality, either shifting from states of blue to greener or intensifying green/brown. Similarly, recent studies of chlorophyll-*a* trends in U.S. lakes have shown algal intensification to be occurring in a relatively small proportion of lakes with long-term field data (Wilkinson et al., 2021). Lakes that did exhibit trends toward greener waters were diverse in their size, shape, watershed area, land cover, and climatic changes. This level of spatial heterogeneity has also been shown in regard to cyanobacteria bloom frequency, where the Rocky Mountain region represented a region where blooms were isolated rather than spatially clustered (Coffer et al., 2021). This result reinforces that interactions between local landscape factors and broader climatic changes can results in heterogeneous, context-dependent responses on freshwater systems (Birk et al., 2020; Jackson et al., 2016).

Notably, the random forest model had a very limited capacity to classify lakes trending toward greener wavelengths (positive trends; Figure S2). These greening lakes tended to be at some of the highest elevations and were sparsely populated by humans relative to the lakes that were blueing (Figure 5). Many of these sites experienced slight increases in winter precipitation and decreases in spring temperature. The six lakes that showed the most substantial changes in lake color (Table S1) had very little in common except that they all have experienced increases in mean summer air temperature (1.0-1.95°C since 1984) and were all shallow (less than 3m mean depth), suggesting that lake color in these systems includes bottom reflectance and possible benthic blooms (Vadeboncoeur et al., 2021). It is possible that shallow lakes are particularly sensitive to changes in water volume via increased evaporation rates due to summer warming, and these reduced water volumes result in an apparent greening. While the slope of the greening trends in color in these 39 lakes were statistically significant, we emphasize that most of the color values were within the range of wavelengths that classify these lakes as "blue" following the approach we used in our spatial analysis. Nonetheless, these lakes appear to be on a "greening" trajectory and the underlying cause of that shift warrants further investigation.

Winter precipitation and spring temperatures, partially explained temporal trends in summer lake color, but they do not fully capture variability in snowpack regimes (Trujillo and Molotch, 2014). In many mountainous areas, winter and spring snowpacks control the length of ice duration (Caldwell et al., 2021), thus changes in these climatic variables can have cascading effects on lake chemistry and ecology (e.g., algal phenology), and thus color (Cavaliere et al., 2021; Hébert et al., 2021). Less snow in combination with warmer summers may interactively stimulate lake production in some lakes (Oleksy et al., 2020; Preston et al., 2016), but these same climatic changes can have the opposite effect on lakes in other regions (i.e., lower phytoplankton biomass; Hrycik et al., 2021), highlighting the need to understand how multiple stressors can have either synergistic or antagonistic effects across lakes.

Finally, there are a few possible explanations for why we did not detect widespread changes in lake color in the region. First, our dataset only included relatively large lakes that were ≥10 ha, but most lakes in the Rocky Mountains are <10 ha (85.3%, n=15,568) and the smallest lakes are more abundant at high elevations (Figure S6). This may partially explain why rates of nitrogen deposition did not appear to have an effect of water color trends, even though excess nitrogen is implicated as a driver of ecological change in high-elevation lakes across the region (Burpee et al., 2022; Moser et al., 2019; Oleksy et al., 2020). Second, we limited our analysis to median summer color, but it is possible that there are dynamics that have helped create the perception of lake greening, such as episodic algal blooms, which are increasing in some systems (Ho et al., 2019; Vadeboncoeur et al., 2021; Wilkinson et al., 2021). This could create issues where algal blooms really are present but are short and intense and thus not captured by Landsat’s 8- or 16-day return sampling interval. As such, algal blooms that are increasing in severity, duration, or magnitude may not be detected by our approach. Conversely, by limiting our analysis to summer months, we may be missing shifts in the phenology of lake color, such as early greening in the spring or a second peak of productivity in the fall (Sommer et al., 2012). Future studies related to lake changes may consider changes and variability in the entirety of the ice-free season. Furthermore, our understanding of regional changes in water quality will be greatly enhanced by advances in the remote sensing of small lakes.

Conclusions

Climate change impacts are likely to influence high-elevation systems faster than others, making high-elevation lakes sentinels of climate change (Adrian et al., 2009; Moser et al., 2019). While eutrophication could pose a major threat to the ability for these systems to continue to provide their vital services to downstream communities, we found that lake color in most large lakes (>10 ha) in this region were stable over the last 35 years. Where we did observe lake color changing, it was consistently towards bluer waters. However, some of the mechanisms for the observed changes, particularly in greening lakes, remain elusive. Future work in this region should investigate the impact of changing water quantity on lake color and how the slow, press changes from climate change interact with short, intense pulse disturbances like floods and fire to alter the ecology of Rocky Mountain lakes and reservoirs.

Conflict of Interest Statement

The authors declare no conflicts of interest relevant to this study.

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Data Availability Statement

The data for this paper comes from the Landsat Archive (via LimnoSat-US 10.5281/zenodo.4139695), LAGOS-US Reservoirs, LAGOS-US NETWORKS, EPA's LakeCat, and The Global Lake Area, Climate, and Population database. All these data are free to download with appropriate links in the bibliography.

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Table 1. Covariates included in the spatial CART model (*) and the temporal Random Forest model (†).

Variable	Mean (sd)	Description	Data source
precip.	47.8 (14.2)	mean monthly precipitation (mm)*	Labou et al., 2020
air temp.	4 (2.8)	mean annual air temperature (°C)*	Labou et al., 2020
population	14,182.4 (166,828.8)	total human population*†	GLCP
LA (km^2)	2.6 (12.9)	lake surface area (km2)*†	NHD
WA:LA	231.8 (894.6)	watershed area:lake area	
WSA	475.7 (2537)	watershed area (km2) *†	NHD
elev.	2,291.9 (571.9)	lake elevation (m) *†	NHD
z_{mean}	4.8 (4.8)	mean lake depth (m) *†	NHD
z_{max}	12.5 (13.3)	max lake depth (m) *†	NHD
NO3 dep.	3.3 (1.4)	total nitrate deposition (2018) *†	NADP
NH3 dep.	1.9 (0.9)	total ammonia deposition (2018) *†	NADP

% ice	0.3 (1.4)	% watershed area classified as ice/snow land cover*†	NLCD
% urban	0.7 (4.8)	% watershed area classified as developed, low+med+high-intensity land use*†	NLCD
% forest	3.7 (9.8)	% watershed area classified as deciduous, coniferous, and mixed forest land cover*†	NLCD
% shrub	31.3 (23.7)	% watershed area classified as shrub/scrub land cover	NLCD
% grassland	18.6 (21.3)	% watershed area classified as grassland/herbaceous land cover	NLCD
% agriculture	2.1 (8.7)	% watershed area classified as crop and hay lake cover	NLCD
% wetland	1.9 (4.7)	% watershed area classified as herbaceous+woody wetland land cover	NLCD
% barren	4.1 (8.6)	% watershed area classified as barren land cover	NLCD
carb.	4 (14.6)	carbonate bedrock*†	LakeCat
sil.	46.9 (44.2)	silicate bedrock*†	LakeCat
slope	25.8 (16)	mean watershed slope angle	LakeCat
CTI	734.7 (110)	mean Composite Topographic Index (CTI) within catchment	LakeCat

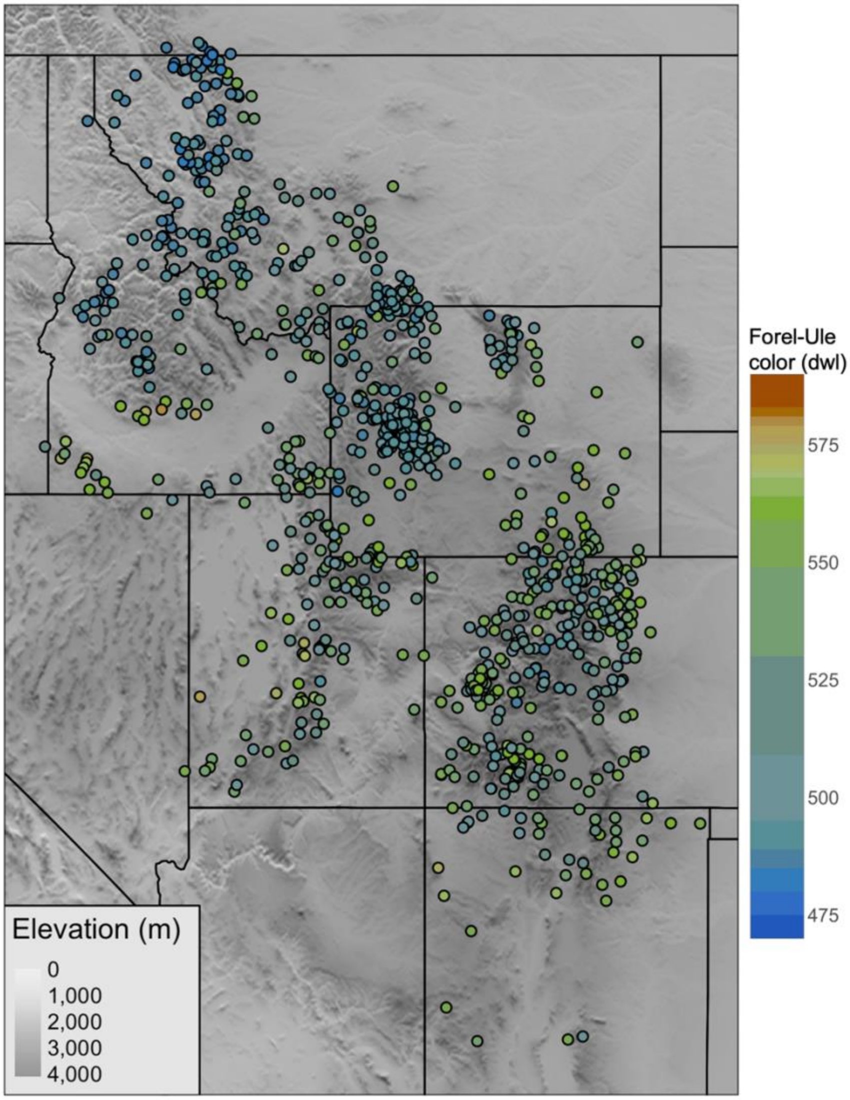

Figure 1: Spatial distribution of median lake color for the study lakes from the modern (2010-2020) period. Lakes are shaded by the 2010-2020 median dominant wavelength (DWL) and its corresponding color on the Forel-Ule scale. Note that individual points are jittered so that points with similar values do not overlap, therefore lake locations are approximate.

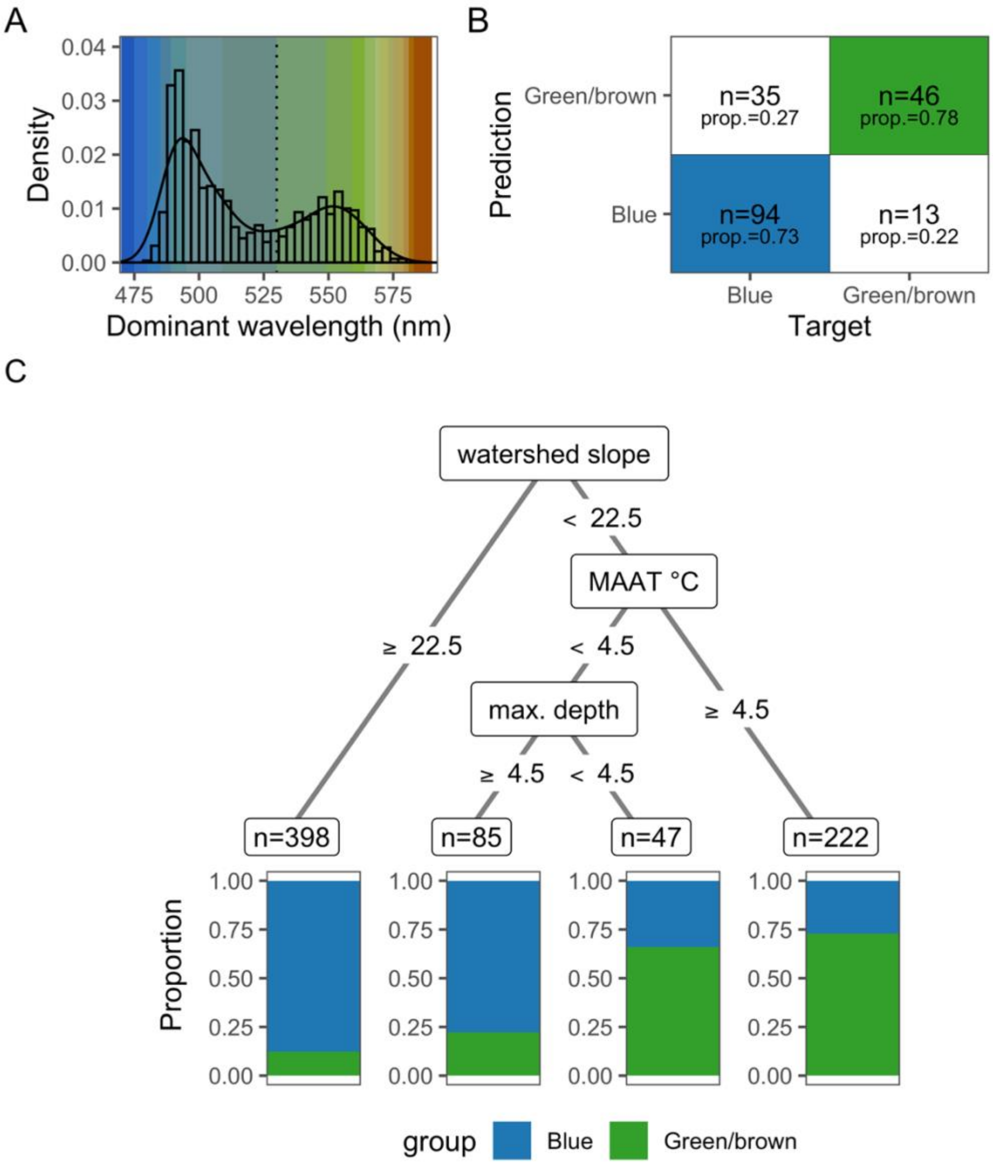

Figure 2: A. Density plot showing the distribution of a median dominant wavelength (2010-2020) where the background color corresponds directly to the Forel-Ule index color. Vertical dashed line represents our threshold for classifying lakes as blue vs. green. **B.** Confusion matrix for the testing data of the spatial CART where true positives for blue/clear classifications are shaded in blue and true positives for green/murky lakes are shaded in green; depicts the accuracy when assigning blue or green lake grouping to a set of lakes that were not used in the training algorithm **C.** CART model

results are visualized in tree form, where the terminal node shows the proportion of blue or green/brown lakes.

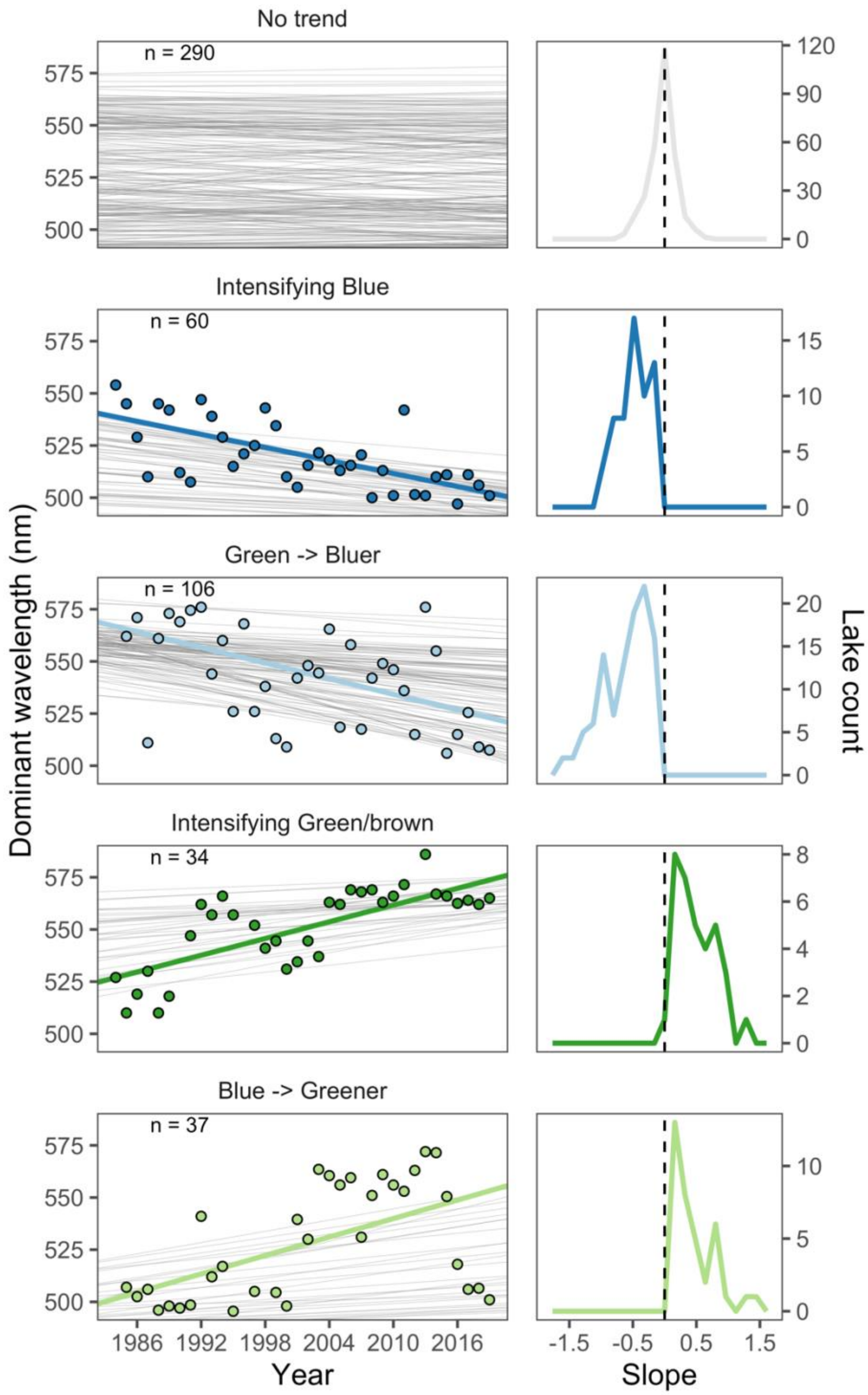

Figure 3. Example trends on the left for each trend category with the corresponding frequency polygons of calculated Sen's slopes on the right.

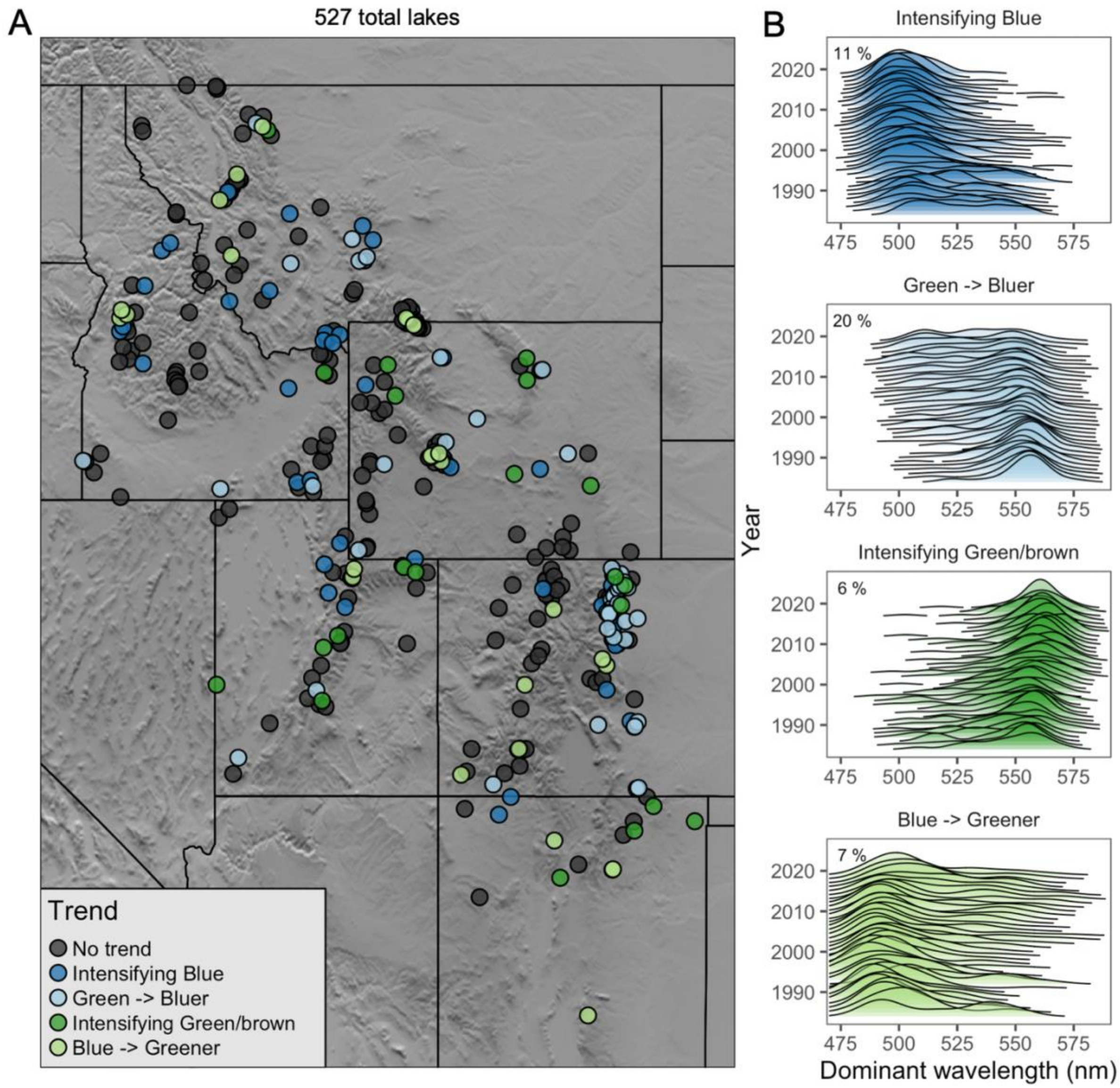

Figure 4. A. Regional map on the left shows where lakes fall into trend categories. **B.** Panels show distributions of dominant wavelength through time in each of the changing trend categories.

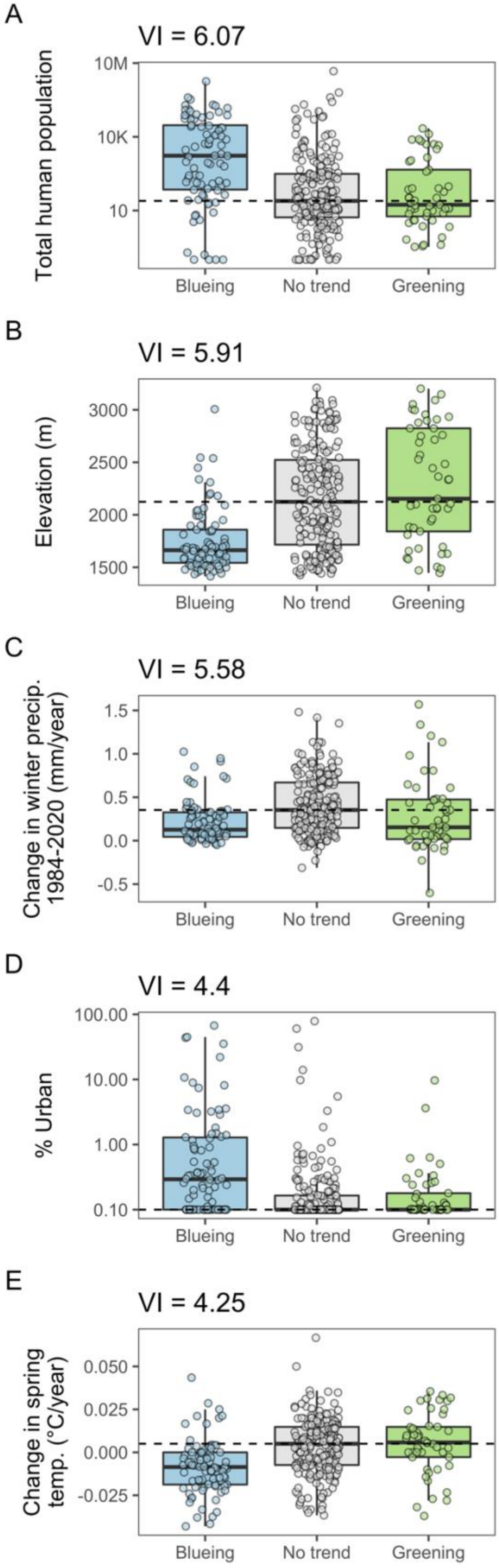

Figure 5 (left). The top 5 variables from highest to lowest based on mean decrease in accuracy from the Random Forest temporal trend classification model. The dashed line shown on each figure is to aid the reader in comparing the different trend categories to the median value for the "No Trend" lakes. Lakes that changed from Green -> Bluer or were Intensifying Blue had negative trends in dominant wavelength while lakes that changes from blue -> greener or were Intensifying Green/brown had positive trends in dominant wavelength.

Supplementary Information for

Title: Heterogenous controls on lake color and trends across the high-elevation U.S. Rocky Mountain region

Authors: Isabella Oleksy[a*], Sarah Collins[a], Samuel J. Sillen[a], Simon Topp[b], Miles Austin[c], Edward K. Hall[c], Catherine M. O'Reilly[d], Xiao Yang[b], Matthew R.V. Ross[c]

[*] Corresponding author; bellaoleksy@gmail.com

[a] Department of Zoology and Physiology, University of Wyoming, Laramie, WY, USA

[b] Department of Geological Sciences, University of North Carolina at Chapel Hill, Chapel Hill, NC, USA

[c] Department of Ecosystem Science and Sustainability, Colorado State University, Fort Collins, CO, USA

[d] Department of Geography, Geology, and the Environment, Illinois State University, Normal, IL, USA

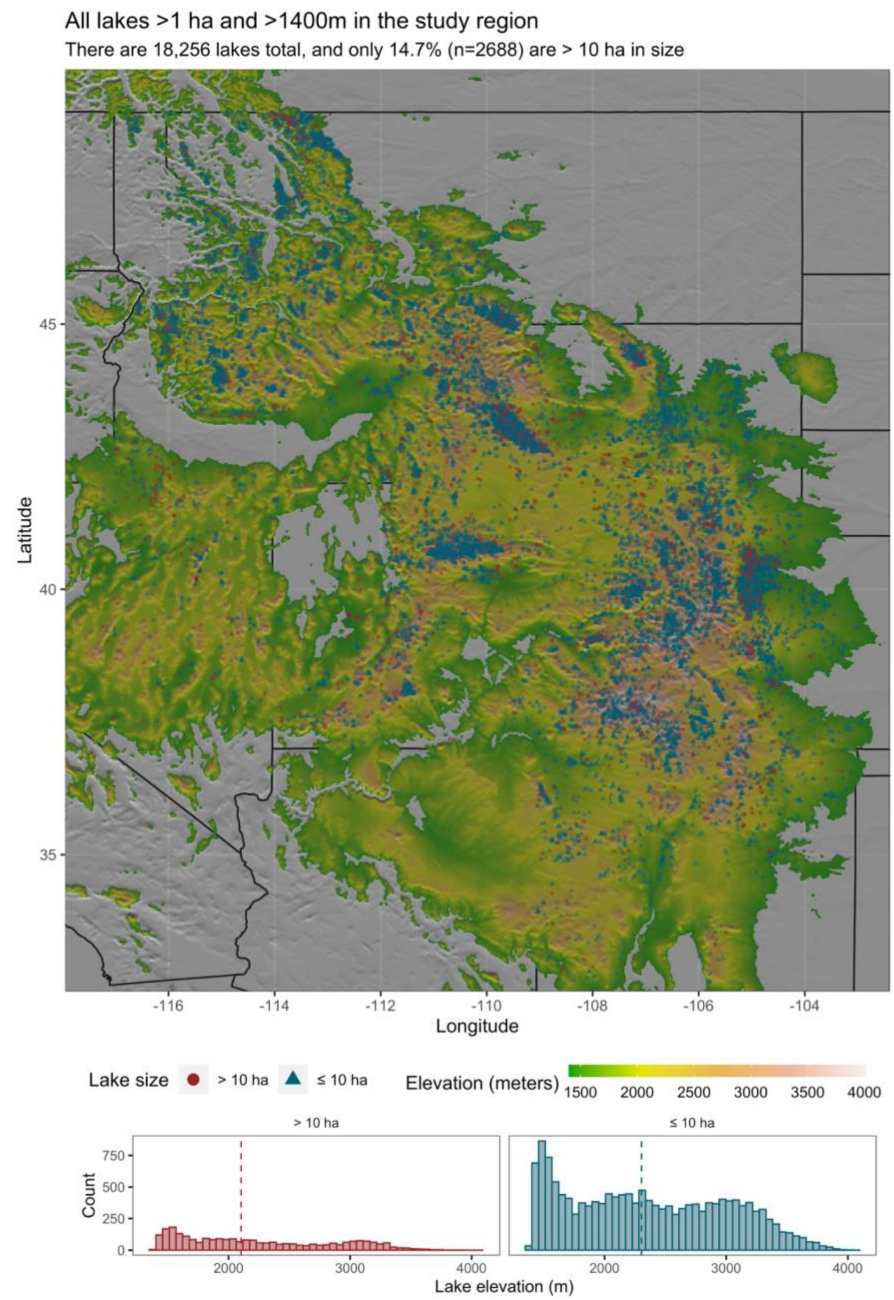

Figure S1. Map of all lakes greater than 1 ha and over 1400 meters elevation in the greater Rocky Mountain region of the United States. Dashed lines on the histograms show the median elevation for each lake size class. Lake size and location from (Smith et al., 2021).

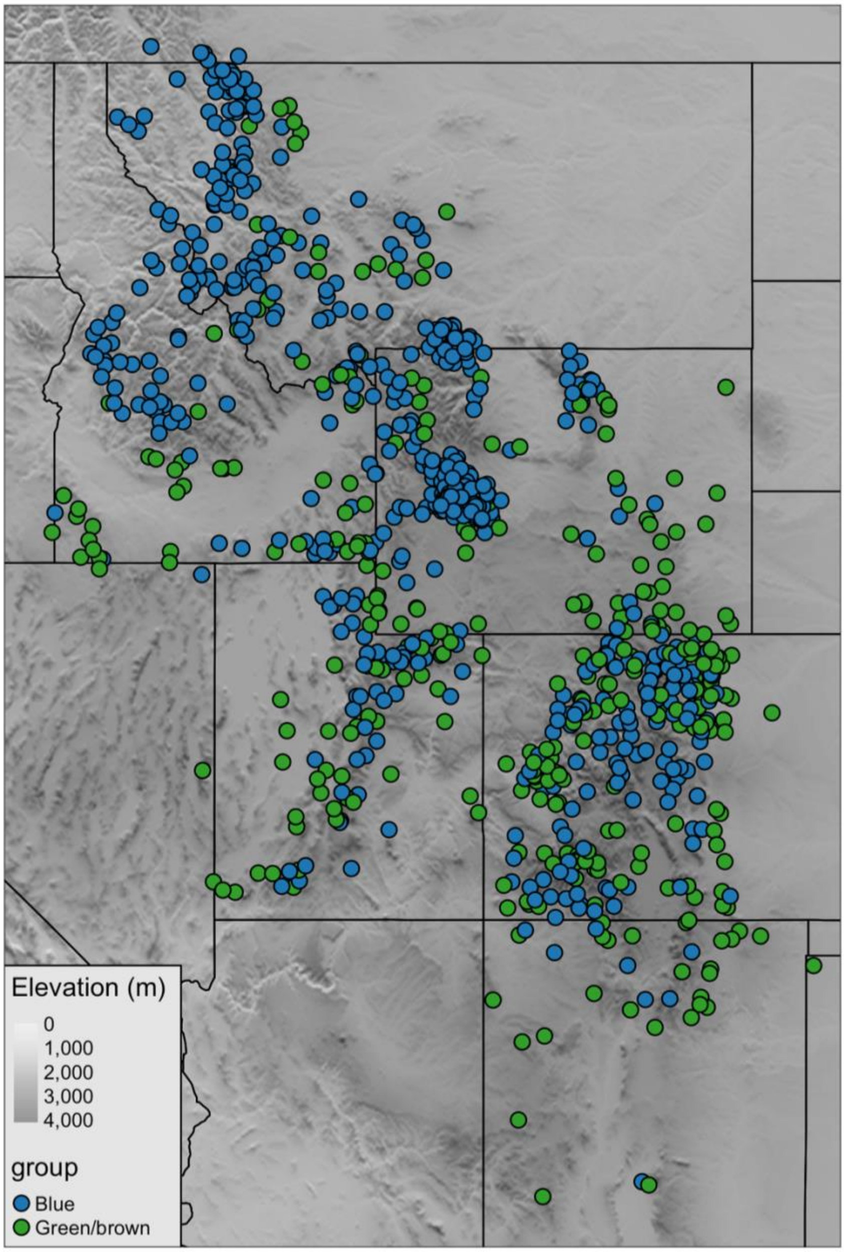

Figure S2. Spatial distribution of median lake color for the study lakes from the modern period (2010-2020) based on a binary classification scheme. Lakes with median dominant wavelength greater than 530 nm were classified as Green/brown while lakes less than 530 nm were classified as generally Blue.

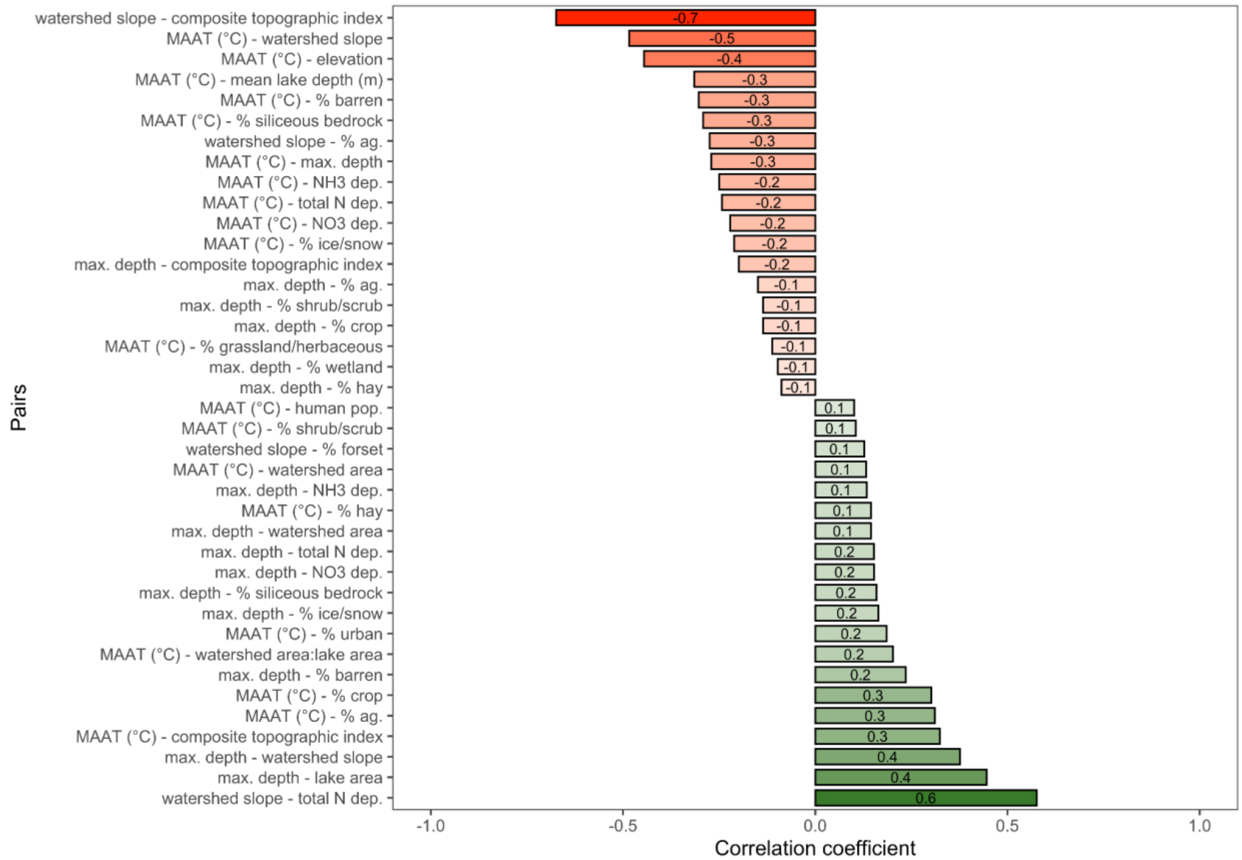

Figure S3. Barplot showing strength of pairwise Pearson correlations between the top 3 explanatory variables in the spatial CART (watershed slope, mean annual air temperature, and maximum lake depth). Only pairwise comparisons with alpha > 0.05 are shown.

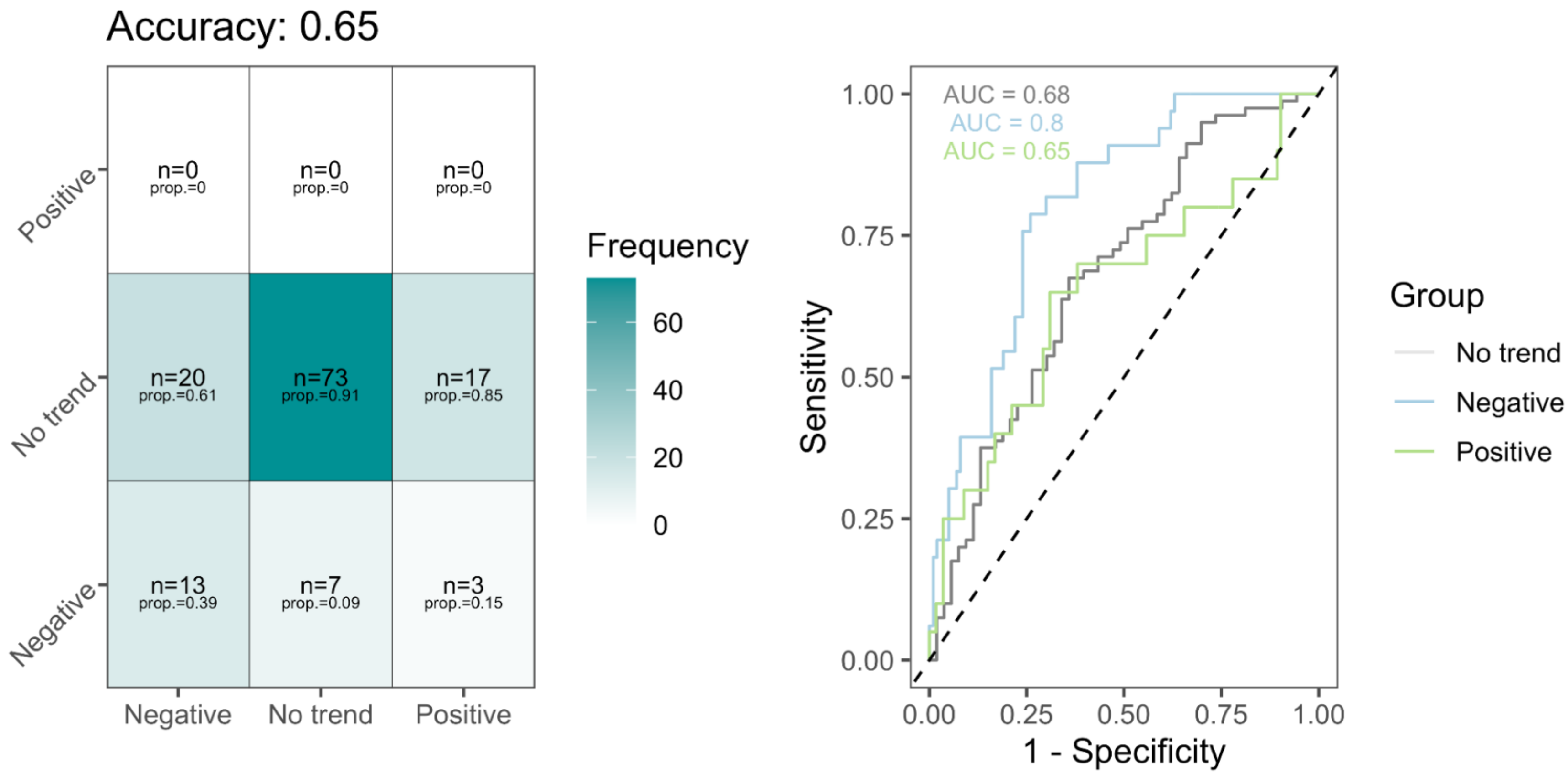

Figure S4. Confusion matrix and ROC curve for the random forest trend classification model.

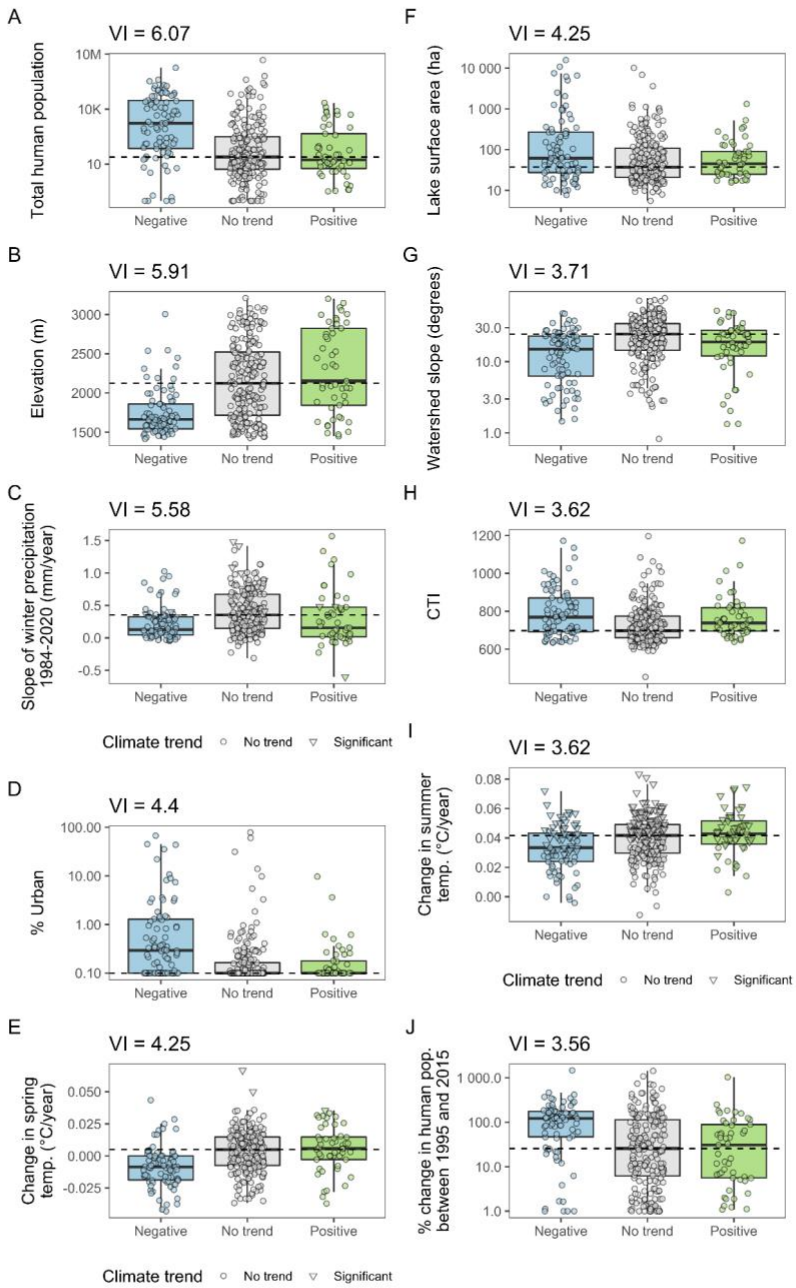

Figure S5. The top 10 variables from highest to lowest based on mean decrease in accuracy from the Random Forest temporal trend classification model. The dashed line shown on each figure is to aid the reader in comparing the different trend categories to the median value for the "No Trend" lakes. In panels C, E, and I the shape of the points denotes whether the Sen's slopes on the winter precipitation, spring, and summer temperatures trends are statistically significant.

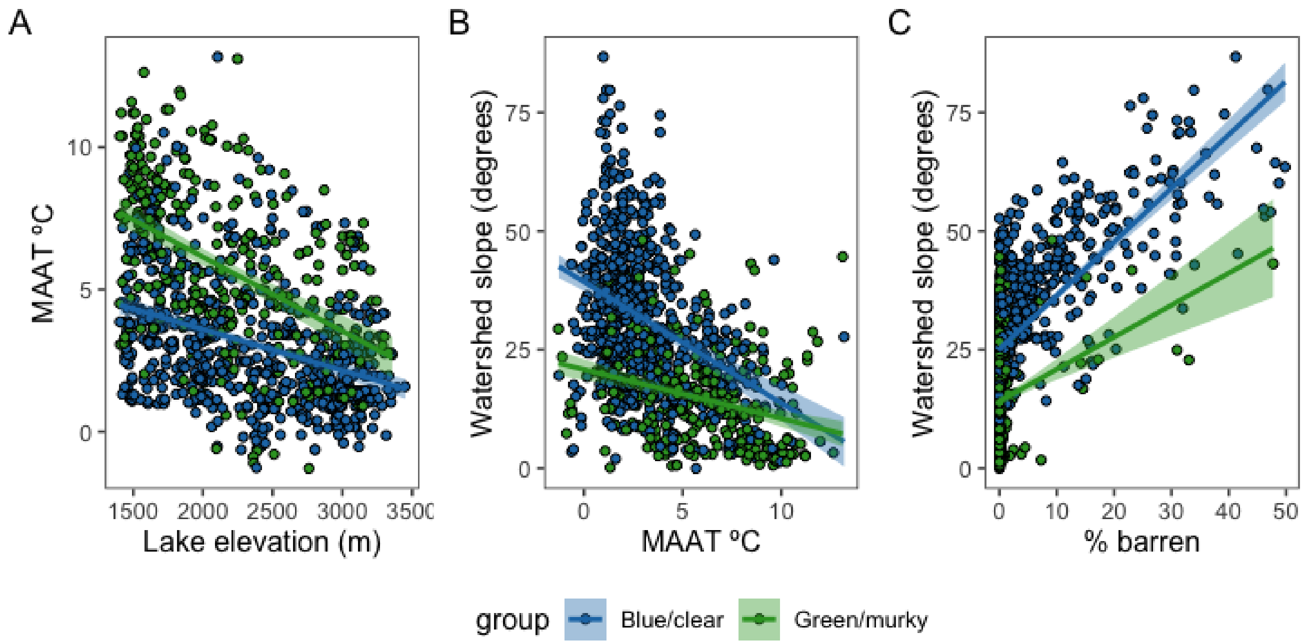

Figure S6. Relationships among key predictors of spatial variability in lake color. (A) Mean annual temperature is negatively correlated with lake elevation. (B) Watershed slope is negatively correlated with mean annual air temperature. (C) Watershed slope is positively correlated with % barren landcover.

Table S1. The subset of lakes in the Blue -> Greener and Green -> Bluer categories which last color shifts such that they were classified as either Green/brown or Blue in the spatial analysis even though early in the record (1984-2005) these lakes would have been classified as Blue or Green/brown (respectively).

Trend	Mode change	Hylak ID	Lake name	State	Lake type	Lat	Lon
Blue -> Greener	Blue to Green/brown	995352	Mitten Lake	MT	Natural lake	-113	48.3
Blue -> Greener	Blue to Green/brown	1060135	Lake David	NM	Natural lake	-105	35.8
Blue -> Greener	Blue to Green/brown	112872	Lake Isabel	NM	Natural lake	-105	35.8
Blue -> Greener	Blue to Green/brown	1055853	Hinman Reservoir	CO	Reservoir	-106	40.2
Blue -> Greener	Blue to Green/brown	1058576	Hermit Lakes	CO	Reservoir	-107	37.8
Blue -> Greener	Blue to Green/brown	1059035	Totten Lake	CO	Reservoir	-109	37.4
Green -> Bluer	Green/brown to Blue	1056066	Unnamed	CO	Reservoir	-105	40
Green -> Bluer	Green/brown to Blue	1055647	Ryan Gulch Reservoir	CO	Reservoir	-105	40.4
Green -> Bluer	Green/brown to Blue	1055851	Clover Basin Reservoir	CO	Reservoir	-105	40.2
Green -> Bluer	Green/brown to Blue	1055926	Left Hand Valley Reservoir	CO	Reservoir	-105	40.1
Green -> Bluer	Green/brown to Blue	1056206	Ralston Reservoir	CO	Reservoir	-105	39.8
Green -> Bluer	Green/brown to Blue	112156	Boulder Reservoir	CO	Reservoir	-105	40.1
Green -> Bluer	Green/brown to Blue	112721	Trinidad Lake	CO	Reservoir	-105	37.1
Green -> Bluer	Green/brown to Blue	1055703	Hertha Reservoir	CO	Reservoir	-105	40.3
Green -> Bluer	Green/brown to Blue	111430	Unnamed	ID	Reservoir	-114	42.2
Green -> Bluer	Green/brown to Blue	1050316	Dougal Reservoir	ID	Reservoir	-117	42.7
Green -> Bluer	Green/brown to Blue	1027810	Wertz Reservoir	MT	Reservoir	-111	46.4
Green -> Bluer	Green/brown to Blue	1031268	Unnamed	MT	Reservoir	-111	46.1
Green -> Bluer	Green/brown to Blue	1050483	McNinch Number 1 Reservoir	WY	Reservoir	-110	42.6
Green -> Bluer	Green/brown to Blue	9066	Boysen Reservoir	WY	Reservoir	-108	43.4

Table S2. For each lake-year, we calculated the mean winter (December-February), spring (March-May), summer (June-August), and fall (September-November) temperature and precipitation trends from PRISM (see *Methods* for details). We calculated the non-parametric Theil-Sen's slope for each lake time series of season precipitation or temperature. In the tables below, we summarized the number of lakes (and percentage of the lakes in each Trend-Model shift combination) that showed substantial trends in precipitation or temperature, using the Mann-Kendall z-score to test for statistical significance at the α = 0.05 level. Dashes (-) indicate that no lakes showed trends in that particular category. Overall, the most widespread climatic trends in the region were increasing summer and fall temperatures. Lakes with color trends classified as Blue -> Greener, nearly every lake has experienced substantially summer warming. Precipitation trends were much more variable, and most lakes have not experienced large shifts in PRISM-estimated monthly precipitation.

			Winter temps.		Spring temps.		Summer temps.		Fall temps.	
Sens slope direction	**Trend**	**Modal shift**	↑	↓	↑	↓	↑	↓	↑	↓
No trend	No trend	No net change	-	-	-	1 (0.3%)	182 (62.8%)	-	206 (71%)	-
Negative	Intensifying Blue	No net change	-	-	-	-	39 (65%)	-	35 (58.3%)	-
Negative	Green -> Bluer	Green/brown to Blue	-	-	-	-	11 (73.3%)	-	10 (66.7%)	-
Negative	Green -> Bluer	No net change	-	-	-	-	56 (62.2%)	-	78 (86.7%)	-
Positive	Intensifying Green/brown	No net change	-	-	-	-	17 (51.5%)	-	28 (84.8%)	-
Positive	Blue -> Greener	No net change	-	-	-	-	27 (87.1%)	-	25 (80.6%)	-
Positive	Blue -> Greener	Blue to Green/brown	-	-	-	-	6 (100%)	-	5 (83.3%)	-

			Winter precip.		Spring precip.		Summer precip.		Fall precip.	
Sens slope direction	**Trend**	**Modal shift**	↑	↓	↑	↓	↑	↓	↑	↓
No trend	No trend	No net change	33 (11.4%)	-	11 (3.8%)	5 (1.7%)	-	16 (5.5%)	2 (0.7%)	-
Negative	Intensifying Blue	No net change	7 (11.7%)	-	3 (5%)	2 (3.3%)	-	-	-	-
Negative	Green -> Bluer	Green/brown to Blue	1 (6.7%)	-	1 (6.7%)	-	-	-	-	-
Negative	Green -> Bluer	No net change	6 (6.7%)	-	9 (10%)	-	-	2 (2.2%)	-	-
Positive	Intensifying Green/brown	No net change	6 (18.2%)	-	3 (9.1%)	-	-	3 (9.1%)	-	-
Positive	Blue -> Greener	Blue to Green/brown	3 (50%)	-	-	-	-	-	-	-
Positive	Blue -> Greener	No net change	1 (3.2%)	1 (3.2%)	-	-	-	2 (6.5%)	-	-

References

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