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The Color of Earth's Lakes

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Key Points:

- ~5.14 million satellite observations over 2013–2020 capture the most common water color for 85,360 global lakes and reservoirs
- Lake color shows strong bimodal distribution, with blue lakes clustered spatially and non-blue lakes more wide-spread at global scale
- Climate and lake properties influence global patterns in lake color, suggesting blue lakes may become less abundant with climate change

Supporting Information:

Supporting Information may be found in the online version of this article.

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Abstract

Although water color is a fundamental property of freshwater ecosystems, the global distribution of lake color remains unknown. Here, we used 5.14 million color records derived from satellite images during 2013–2020 to determine the modal water color of 85,360 representative lakes worldwide. We find that globally, lake modal colors span the visible spectrum with a bimodal distribution of blue versus non-blue (green-brown), with 31% of lakes being blue and 69% being non-blue. Both climate and lake morphology influence lake modal color. Blue lakes are associated with cooler summer air temperature, winter ice cover, and higher precipitation. Under a 3°C increase in summer air temperature, 14% of blue lakes could shift to a non-blue regime, representing a substantial change to their underlying ecology. As lake ecosystems continue to face a range of stressors, this study provides a critical baseline for understanding lake responses to global environmental change.

Plain Language Summary

Water color is a reasonable approximation of water quality. Scientists have studied lake water color for over a century, but we still do not know the color of the lakes across the whole Earth. We used satellite images to determine the water color of 85,360 lakes found around the world. We found that most lakes look green or brown. Blue lakes are not very common. Blue lakes are found in places where the summer temperatures are cooler. Blue lakes are also likely to be covered by ice in winter and are generally deeper than lakes that have green or browner water colors. So, if the summer temperatures get warmer or winter temperatures get so warm that there is no more lake ice, some lakes that are currently blue might shift to being green or brown. Projecting into the future, we predict that 1 in 10 blue lakes might change color because of warming air temperatures. These changes in water color probably indicate a change in the water quality and the conditions for fish in those lakes. We can use satellite images to track changes in lake water color into the future to help us understand how water quality is changing.

1. Introduction

Water color influences the cultural and economic value of water bodies (Schirpke et al., 2021; Smith & Davies-Colley, 1992; Votruba & Corman, 2020), and blue lakes are typically perceived as pristine (Tyler, 1965). One of the oldest ecosystem measurements (Forel, 1895; Juday & Birge, 1933; Ule, 1892), water color has also been recognized by the current Global Climate Observing System as an Essential Climate Variable (Mason et al., 2010) and is the variable most closely related to lake ecosystem properties. Because it can be directly observed by satellites, water color provides the potential to detect environmental changes in lakes in remote regions and at global scales, allowing us unprecedented opportunities to examine global patterns in lake ecosystems. However, despite humans' long fascination with the color of water (Conte, 1881; Crosby, 1884; Tyndall, 1870), we do not know how lakes of different colors are distributed around the globe.

Although recent studies have used water color to identify trends in lakes and rivers (Gardner et al., 2021; Hou et al., 2022; Leech et al., 2018), factors that could influence these trends have not been directly identified. Studies of spatial and temporal patterns in inland water color at regional to continental scales hint at controls such as latitude, elevation, landscape, and lake morphometry (Gardner et al., 2021; Giardino et al., 2019; Lehmann et al., 2018; Topp, Pavelsky, Dugan, et al., 2021). Since lake ecosystems are influenced by hydrological connectivity and land cover (e.g., Webster et al., 2008) as well as internal biogeochemical processing (e.g., Köhler et al., 2013), climate factors such as precipitation and temperature likely play a key role in influencing lake water color. However, the role of climate in controlling lake color remains unknown and is critical to understand under a changing climate.

2. Methods

Using a representative population of Earth's lakes and reservoirs (hereafter "lakes"), we determine the distribution of modal lake color globally, explore its spatial patterns, and examine the potential role of climate in affecting color. We calculated the modal color for 85,360 lakes based on dominant wavelength values over a 7 year period (2013–2020). Dominant wavelength was estimated from Landsat 8 OLI bands (Lehmann et al., 2018; Van der Woerd & Wernand, 2018) for the center of each lake (Shen et al., 2015; Topp, Pavelsky, Dugan, et al., 2021; Topp, Pavelsky, Stanley, et al., 2021) during ice-free and cloud-free conditions, excluding lakes whose color had the potential to be influenced by reflectance from the lake bottom (see Text S1–S2 in Supporting Information S1 for detailed method description). We used color at lake center to focus on pelagic conditions and to remove the influence of shoreline vegetation, shallow water, lake area variation, or riverine influence. Subsequently, for lakes with ≥20 observations, modal color (i.e., the most common color, hereafter referred to as lake color) was determined as the wavelength of the highest peak in the dominant wavelength density distribution. More details on the distribution of lakes and the methods are provided in Supporting Information S1.

Due to the large contrast in lake areas, the sheer number of studied lakes, and the limited resolution that can be presented in a figure, it is challenging to visualize lake modal color for each lake at the global scale. Instead, we aggregated lake modal color in 3° longitude by 2° latitude grid cells covering 180°W–180°E longitude and 60°S–90°N latitude. For each grid cell, we estimated the median lake color and the spatial color variability represented by the standard deviation of the modal colors in that grid (also see method flowchart in Figure S1 in Supporting Information S1). We chose not to weight our calculation of median color by lake area to reflect the overall diversity of lakes within each cell; small lakes, though very numerous and quite important, are often overlooked in the global lake literature, and we chose not to inherently value large lakes more than small lakes. Lake-scale color distribution for a few selected regions are presented in Figure S2 in Supporting Information S1, with an app (https://eeproject.users.earthengine.app/view/cool) allowing exploration of the data at lake scale.

To investigate climate and geomorphological factors affecting lake color at the global scale, we used annual and seasonal air temperature and precipitation calculated from ERA5 climate reanalysis data (Copernicus Climate Change Service Climate Data Store, 2017) along with lake elevation, surface area, volume, and mean depth in a regression tree analyses to interpret key factors influencing lake color (see Text S3 and Table S1 in Supporting Information S1 for detailed variable selection and description). We chose these variables because they are available at the global scale. Since the regression tree indicated that in the wetter regions (monthly precipitation ≥55 mm), the likelihood of a lake being blue was temperature-dependent, we explored how a change in only summer temperature may influence lake modal color in this wetter climate. To estimate how many of these lakes might change color from blue to non-blue, we made projections for +1, +2 and +3°C to bracket the expected temperature increase by 2100 (IPCC, 2021).

For all visualizations, we used the corresponding colors from the Forel-Ule Index (Wang et al., 2018; Wernand and van der Woerd, 2010), as they contain realistic information on brightness and saturation in addition to the wavelength, thus they more closely resemble the perceived water color.

3. Results

Broadly, we find that blue lakes are dominant in only a few regions on Earth, whereas green and brown lakes are common and widely distributed (Figure 1). Globally, lake modal color has a bimodal distribution that distinguishes blue lakes (peak at 495 nm) from green and brown lakes (peak at 572 nm) at the anti-modal value of 526 nm (Figure 1 inset). Similar bimodal distributions in lake color have been found in regional studies in Italy (Giardino et al., 2019) and New Zealand (Lehmann et al., 2018). Overall, blue lakes comprise only 31% of lakes and are dominant in only 16% of Earth's landscape (at grid scale, see Figure 1). Blue lakes tend to cluster in cool and high altitude regions (e.g., northern Europe, Himalaya and the Tibetan Plateau, Rocky Mountains,

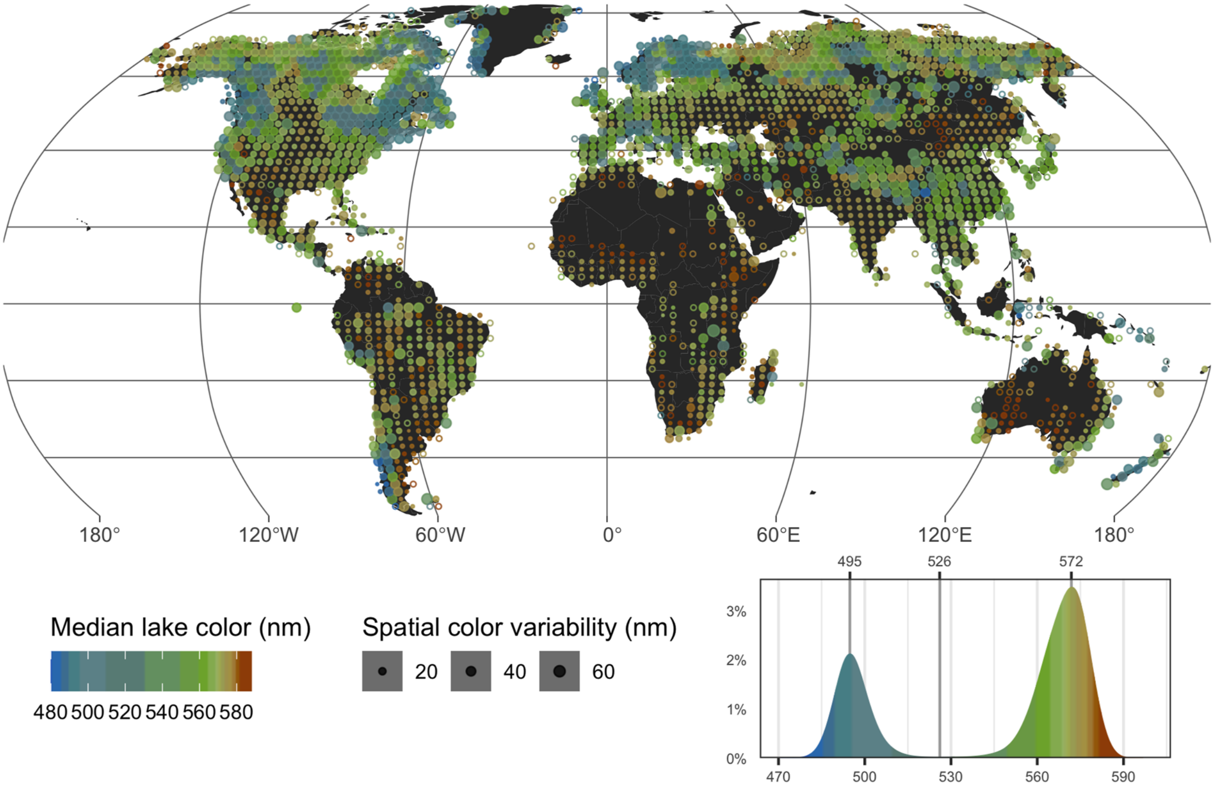

Figure 1. Spatial distribution of median lake modal color and spatial variability across lakes. Median and variability are summarized for lakes in each 3° longitude by 2° latitude rectangular grid. Size of the filled circles denotes spatial lake color heterogeneity. Open circles indicate grid cells with only one lake, thus variability cannot be calculated. There is no relationship between the number of lakes within a grid and the variation of lake color in that grid (Figure S3 in Supporting Information S1). Enlarged regional-scale maps for selected locations are presented in Figure S2 in Supporting Information S1 and an interactive app has been developed to assist close examination of the color at lake scale (https://eeproject.users.earthengine.app/view/cool). Inset (lower-right): lake color density distribution (Gaussian kernel bandwidth = 3 nm) for 85,360 globally distributed lakes using color data between 2013 and 2020. Areas under the density distribution are colored using the corresponding color associated with the Forel-Ule Index and are consistent with the color scale of the map. Grid cell area ranges from 74,000 km^2 at the equator to 17,000 km^2 in the high latitudes.

northeastern Canada, Patagonia, New Zealand, Figure 1), while green and brown lakes tend to distribute along coastlines, in continental interiors and in drier regions (Figure 1).

The broad patterns in lake modal color are accompanied by smaller scale variation across lakes, suggesting that both large- and small-scale factors influence lake color. Lake water color is likely driven by combinations of climate, geology, soil, and vegetation, which operate at different scales to affect the types and magnitudes of terrestrial inputs to aquatic systems. Lakes in high latitudes, alpine regions, and to a certain extent, the tropics tend to differ from their neighbors in color (Figures 1 and S4 in Supporting Information S1). Color among groups of lakes can be highly variable, such that blue lakes can be found adjacent to green and brown lakes (Figure S2 in Supporting Information S1). Such spatial heterogeneity in lake modal color is likely driven in part by landscape variability in hydrogeomorphometric settings that are not well-resolved at regional and global scales. These findings emphasize the importance of understanding multiscale drivers of ecosystems states (Soranno et al., 2019).

A regression tree analysis indicates that blue lakes share similar climatic and geomorphometric conditions. Most blue lakes are found in association with relatively high precipitation and cool summers or are deeper lakes situated at higher elevation (Figure 2). In places where summer air temperatures are cooler than 19°C, 35.7% of lakes are blue, compared to only 9.4% blue lakes in areas with warmer summers, indicating that blue lakes are ~4 times more likely to occur in cooler climates (Figure S5 in Supporting Information S1). In other studies, cooler summer air temperatures have been associated with lower summer chlorophyll-*a* (Shuvo et al., 2021) and higher summer water clarity (Collins et al., 2019). Cooler summer temperatures would curtail algal growth, maintaining clearer (bluer) water.

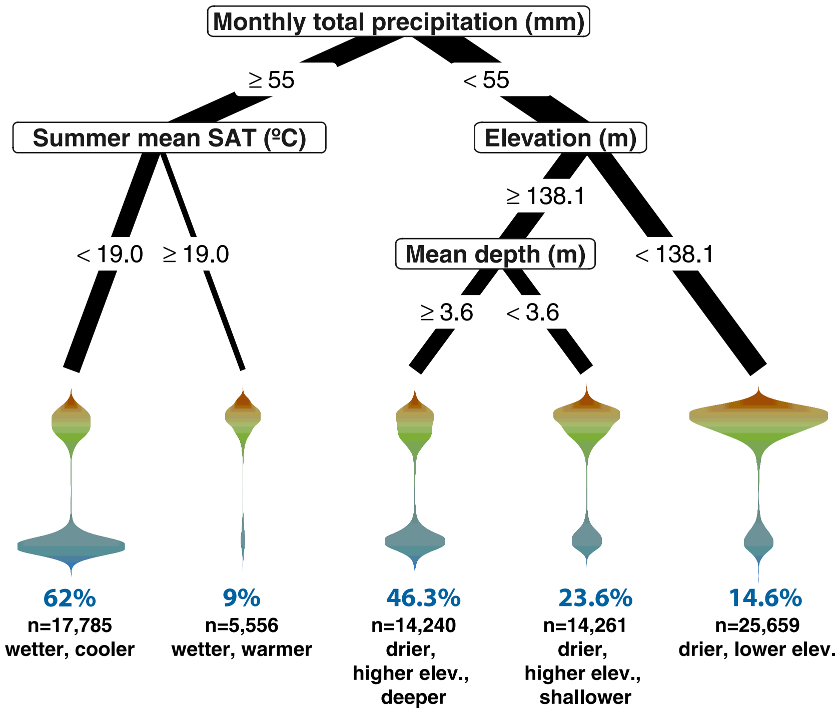

Figure 2. Regression tree showing how climate and geomorphometric factors affect lake color. Violin plots show the distribution of lake color at each node followed by the percentage of blue lakes, the total number of lakes and node description. Colors of the violin plot follow the FUI color as shown in Figure 1. The global spatial distribution of the lakes in each node is shown in Figure S5 in Supporting Information S1. Climate summary data were calculated for the same period 2013–2020 as the lake color data.

Winter ice cover may also be an important characteristic of blue lakes. The summer mean air temperature threshold of 19°C in the regression tree corresponds to a mean winter air temperature of −7.7°C (Figure S6 in Supporting Information S1); thus, lakes in these cooler summer regions likely experience winter ice cover. Of these lakes, 34.1% are blue, compared to 16.9% blue lakes in warmer regions, making ice-covered lakes approximately twice as likely to be blue. Globally, there is a large decrease in the proportion of blue lakes above this temperature threshold (Figure 3). Winter conditions are known to influence the summer lake environment (Hampton et al., 2017), and winter ice-covered lakes may have relatively bluer summer water color due to slower, delayed phytoplankton growth that reduces biomass. Cold winters may also impact biogeochemical processes and reduce nutrient availability and terrestrial inputs.

Across all climate conditions, deeper lakes are more likely to be blue than shallow lakes (Figures 2 and 3). Similar results were found in New Zealand, where blue lakes tended to be deep (>50 m) and at high elevation (>300 m) and more than 95% of shallow lakes (<5 m depth) were green-to-brown (Lehmann et al., 2018). Global and regional studies have also found that lake depth is a predictor of chlorophyll-*a* (Shuvo et al., 2021) and water clarity (Lottig et al., 2017). Lake depth has emerged as a critical attribute of lake ecosystems in several global studies, highlighting the key role depth plays in physically structuring lakes through its effect on long-term warming trends (O'Reilly et al., 2015), the loss of winter ice cover (Sharma et al., 2019), and the onset and strength of stratification (Woolway et al., 2021), each of which can influence biogeochemical processes and lake ecosystem conditions.

As summer temperatures become warmer, and loss of winter ice cover continues, blue lakes in regions of high precipitation may be less likely to persist. In these wetter regions, blue lakes are highly unlikely to occur when mean summer temperatures increase above 19°C (blue lake ratio declines from 62% to 9% between the leftmost two leaf nodes in Figure 2). Our temperature projections show that lakes that are susceptible to color shifts away from blue are primarily located in northeastern North America and northern Europe (Figure 4). This summer warming could lead to up to 14% of lakes shifting modal color away from blue. While not intended to be a comprehensive assessment of color change due to warming, these predictions nonetheless chart the likely pathway of

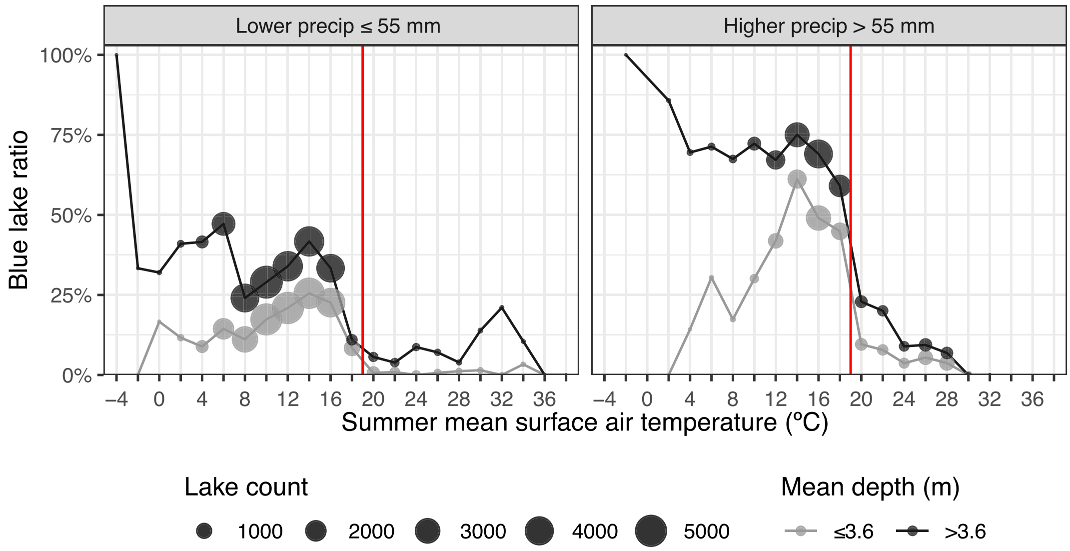

Figure 3. Percent blue lakes found in areas of high and low precipitation, for shallow and deep lakes, at different summer mean surface air temperatures (ºC, *x*-axis). Binning of precipitation (mm) and depth is based on decision tree thresholds in Figure 2; and binning for summer temperature is at 2°C intervals with *x*-axis labels showing the center values for each bin. Red vertical line indicates summer mean air temperature of 19°C as suggested by the regression tree model in Figure 2. This 19°C summer temperature corresponds to a winter mean surface air temperature of −7.7°C (see Figure S6 in Supporting Information S1); lakes experiencing temperatures lower than this likely have seasonal ice cover.

color shift for lakes whose colors are more likely affected by future warming. Consistent with these predictions, changes in precipitation and temperature have already been associated with trends in lake greenness in the Boreal Arctic (Kuhn & Butman, 2021), underscoring the potential for shifts in lake color with climate change.

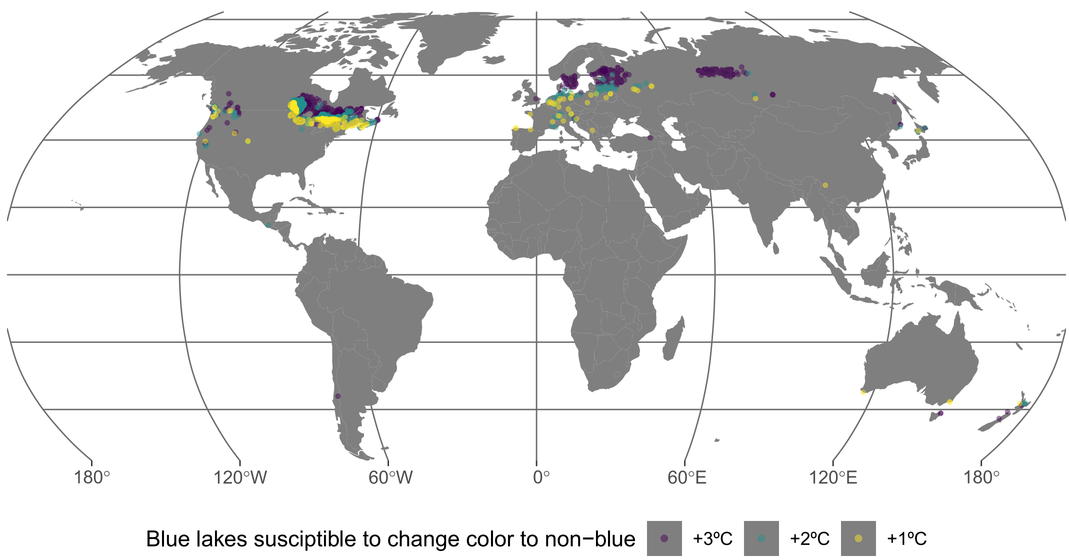

Figure 4. Lakes susceptible to a potential color shift due to climate warming ($n = 3{,}771$). Blue lakes in the first leaf node of Figure 2 that are at risk of shifting to non-blue colors with summer mean surface air temperature increasing by 1°C ($n = 513$), 2°C ($n = 1{,}351$), and 3°C ($n = 1{,}907$) to cross the 19.0°C. Color represents the degree of warming summer mean surface air temperature needed to cross the 19.0°C threshold.

4. Conclusions

Our results underscore that lake modal water color is sensitive to climate conditions. Globally, our results suggest that climate change may decrease the percentage of blue lakes. Shifts in lake modal color from blue to green or brown, and vice versa, likely represent a substantial change in ecosystem structure and function (e.g., Hayden et al., 2019; Murdoch et al., 2021; Topp, Pavelsky, Dugan, et al., 2021; Topp, Pavelsky, Stanley, et al., 2021). The nature and mechanisms of these trajectories of change are unknown, and cross-scale interactions between climate change and local controls may lead to nonlinear dynamics and tipping points in lake ecosystems. As an integrative measure of biological and physical conditions within lake ecosystems, water color contains a wealth of information related to clarity (Garaba et al., 2015; Nürnberg & Shaw, 1998; Topp, Pavelsky, Stanley, et al., 2021), turbidity (Garaba et al., 2015), colored dissolved organic matter (Garaba et al., 2015; Nürnberg & Shaw, 1998), chlorophyll (Nürnberg & Shaw, 1998; Webster et al., 2008) and productivity (Nürnberg & Shaw, 1998), as well as phenological shifts (Topp, Pavelsky, Dugan, et al., 2021) and trophic state (Wang et al., 2018). Monitoring lake water color as an Essential Climate Variable (Mason et al., 2010) will be crucial for understanding the impact of climate and land use change on lakes into the future.

Data Availability Statement

The global lake color data set is available on Zenodo (https://doi.org/10.5281/zenodo.6394574). All code used in analysis and figure making for this paper are available at https://doi.org/10.5281/zenodo.6807573. R statistical software (R Core Team, 2022) and packages tidyverse (Wickham et al., 2019), sf (Pebesma, 2018), and rpart (Therneau & Atkinson, 2022) were used in carrying out statistical analysis and generating figures in this paper.

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