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Rapid and highly variable warming of lake surface waters around the globe

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Key Points:

- Lake surface waters are warming rapidly but are spatially heterogeneous
- Ice-covered lakes are typically warming at rates greater than air temperatures
- Both geomorphic and climate factors influence lake warming rates

Supporting Information:

- Figures S1–S4 and Tables S1–S4

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Abstract In this first worldwide synthesis of in situ and satellite-derived lake data, we find that lake summer surface water temperatures rose rapidly (global mean = 0.34°C decade^{-1}) between 1985 and 2009. Our analyses show that surface water warming rates are dependent on combinations of climate and local characteristics, rather than just lake location, leading to the counterintuitive result that regional consistency in lake warming is the exception, rather than the rule. The most rapidly warming lakes are widely geographically distributed, and their warming is associated with interactions among different climatic factors—from seasonally ice-covered lakes in areas where temperature and solar radiation are increasing while cloud cover is diminishing (0.72°C decade^{-1}) to ice-free lakes experiencing increases in air temperature and solar radiation (0.53°C decade^{-1}). The pervasive and rapid warming observed here signals the urgent need to incorporate climate impacts into vulnerability assessments and adaptation efforts for lakes.

1. Introduction

Lakes hold a large majority of Earth's liquid freshwater, support enormous biodiversity, and provide key provisioning and cultural ecosystem services to people around the world. Climate change is among the greatest threats to lakes [*Carpenter et al.*, 2011], yet empirical knowledge of global lake responses remains fragmented, in need of the syntheses that already have catalyzed major climate change initiatives for marine, terrestrial, and atmospheric systems. Previous analyses have been restricted to temperature trends in either remotely sensed or in situ data, each of which have geographic and morphological biases. For example, satellite-inferred water temperature data are generally restricted to lakes >10,000 ha [*Schneider and Hook*, 2010; *MacCallum and Merchant,* 2012] omitting >90% of the world's lakes that are small and shallow and may respond differently to climate change [*Wetzel*, 1990; *Winslow et al.*, 2015], and previous efforts using in situ data tended to be geographically restricted, primarily in north temperate latitudes (e.g., [*Livingstone and Dokulil*, 2001; *Austin and Colman*, 2007]). As a result, while there is sufficient evidence to indicate the effects of climate change for individual lakes or lake regions, there is limited understanding of large-scale spatial patterns in lake responses or how those patterns are influenced by various climatic and geomorphic factors. By integrating satellite and in situ surface water temperature trends for lakes worldwide, we were able to balance the biases inherent to each data type [*Hampton*, 2013], capturing broad spatial coverage as well as geomorphic variability across a range of lake sizes (Figure S1 and Table S1 in the supporting information).

Understanding the trajectories of temperature change in inland waters is a foundational step in advancing science on a broad diversity of societally important issues. Even seemingly small changes in lake temperature profoundly affect key physical and biological processes through nonlinear dynamics [*Adrian et al.*, 2009]. The diverse array of lake sizes and shapes on earth suggests that patterns of lake warming should be highly variable, both in space and time. Key drivers of surface water temperature include absorbed solar irradiance and heat exchange with the atmosphere, which is controlled by air temperature, solar radiation, humidity, ice cover, and wind [*Edinger et al.*, 1968], but is also mediated by local factors such as lake surface area and depth [*Schmid et al.*, 2014]. These morphometric factors vary enormously across lakes, and recent rates of change in climate variables are also spatially heterogeneous [*Wild*, 2012; *Eastman and Warren*, 2013; *Ji et al.*, 2014]. Accordingly, we examined relationships between lake surface temperatures and climatic and geomorphic drivers in order to better understand and predict global trends of lake warming.

2. Data and Methodology

2.1. Data Set

We used a database that incorporates lake summer surface water temperatures (LSSWT) and climate variables (air temperatures, radiation, and cloud cover) from 1985 to 2009 [*Sharma et al.*, 2015]. The database includes

LSSWT derived from in situ and/or satellite measurements, providing a global distribution of lake data. LSSWT were calculated as 3 month mean temperatures. Generally, for lakes situated in the Northern Hemisphere, summer was defined as the period 1 July–30 September (JAS), whereas in the Southern Hemisphere summer was 1 January–31 March (JFM). Exceptions were latitudes less than 23.5°, for which the JAS metric was used south of the equator, and the JFM metric was used north of the equator to avoid the cloudy wet season in the tropics allowing for an increased number of cloud-free satellite observations [*Schneider and Hook*, 2010; *Sharma et al.*, 2015]. The only exception to this time period were the in situ data for Toolik Lake, Alaska, for which June–August were used due to the early onset of winter in September at this high latitude. In situ data are point collected, whereas the satellite data represent an areal mean of at least 9 km^2. We chose lakes for which there were at least 13 years of data (118 in situ sampled lakes and 128 satellite-sampled lakes; there were 11 lakes sampled by both in situ and satellite methods) (Table S2). These lakes had data relatively evenly distributed across the 25 year time period and were not missing data at the beginning and the end of the time period. The median record length was 22 years; the 75% quartile was 24, and the 25% quartile was 19 years.

Metadata for each lake included latitude, longitude, elevation, surface area, volume, mean depth, and maximum depth for each lake as well as climate variables [*Sharma et al.*, 2015]. Air temperature was gridded data at 0.5° resolution from Climatic Research Unit time series version 3.21. Surface solar radiation data were o the 1° × 1° satellite product from NASA/Global Energy and Water Cycle Experiment Surface Radiation Budget shortwave radiation data set version 3.0 available from 1985 to 2007. Cloud cover were from a 1° regridded version of the NOAA 5-channel Advanced Very High Resolution Radiometer cloud imagery record with percent coverage statistics derived using Pathfinder Atmosphere's Extended processing system [*Heidinger et al.*, 2010; *Stubenrauch et al.*, 2013].

2.2. Global Average Rate of Change and Trend Calculations

The global average warming rate for lake summer surface water temperatures was calculated following the approach used by the International Panel on Climate Change [*Hartmann et al.*, 2013a, 2013b]. For each lake, we calculated the temperature anomalies relative to its 1985–2009 mean. We then used linear regression across the annual globally averaged anomalies to determine the global LSSWT warming rate. For lakes with both in situ and satellite temperature data, we used only the in situ values. Calculations were done in *R* [*R Development Core Team*, 2014]. For each individual lake, we used Sen slopes to calculate trends in LSSWT, air temperature, cloud cover, and shortwave radiation. To obtain the most robust trends for each variable, we used all available data and did not gap-match across data sets. Sen slopes and significance were calculated in R using the "openair" package [*Carslaw and Ropkins*, 2012] (Table S2). A variety of sources contribute uncertainty to individual lake trends (Table S2); however, given that our approach is to compare trends across lakes, noise is more likely to obscure patterns rather than to create them.

2.3. Proximal Similarity Analysis

A proximal similarity analysis was completed using the Getis-Ord Gi* statistic, and resulting maps were generated in ArcGIS 10.2. This analysis identified subcontinent regions on the globe where lake temperatures were trending similarly to surrounding lakes within that area relative to the global trend. The Getis-Ord Gi* statistic is a *z* score based on two characteristics for each lake: its trend value (Sen slope) and its proximity to other lakes with similar values. This is computed by, first, summing one point value and that of a number of proximal observations within an approximately 1300 km radius (a subcontinent regional sum). That regional sum is then compared proportionally to the sum of the global data set. Such a comparison results in a *z* score for each observation, and observations with a regional sum significantly higher or lower than the global sum are considered to have statistically significant regional similarity above or below the global trend. In other words, statistically significant high or low *z* scores identify high clustering of point locations with high or low values within the data set [*Getis and Ord*, 1992; *Ord and Getis*, 1995; *ESRI*, 2013]. The distance of 1300 km was determined by computing the average distance that included at least 5% of the total input lake temperature points in the aggregate data set. This means that even in areas where data points are less dense (e.g., South America and Africa), one lake will still be compared in the analysis with a handful of regional neighbors. The Getis-Ord Gi* statistic is computed using a false discovery rate correction to resolve multiple testing and spatial dependency concerns in the data set [*Caldas de Castro and Singer*, 2006; *ESRI*, 2013]. This process generates a *z* score and *p* value for each lake. For visualization purposes, we used the *z* score of each lake point to generate a kernel density layer showing regions wherein exist a statistically significant density of lake points with similar temperature trends (high or low).

In our case, the hotspot analysis identified lakes with high or low temperature trends within the global data set that are in close proximity to other lakes with similarly high or low temperature trends. Because this analysis is based on the distribution of the data, an identification of a cool spot does not necessarily mean these are cooling areas. Rather, it means they are areas of concentration of lakes with trends less than the mean of the data set. Areas that are labeled nonsignificant do not have a statistically significant relationship between their trend and proximity to other lakes with similar trends.

2.4. Regression Tree of Lake Temperature Trends

A regression tree analysis was performed on LSSWT trends to identify suites of factors that correspond with the warming trends observed across the widely distributed lakes in our database. Prior to conducting these analyses on LSSWT trends, we used preliminary models of interannual variation in LSSWT to assess whether the available set of environmental variables offers reasonable predictions of surface temperature in any given lake for any given year. Predictors included winter and summer mean air temperature, % cloud cover, and shortwave radiation, as well as geomorphic characteristics of the lakes (elevation, surface area, and maximum depth) and we tested three regression model approaches (Table S3). Subsequently, in the regression tree analyses, we included trends in winter and summer air temperature, % cloud cover, shortwave radiation, geomorphic characteristics, and mean winter air temperatures (as a proxy for ice cover). We included winter climate trends because some regions are experiencing greater climate change during the winter, and winter conditions can strongly influence summer water temperatures. Regression trees iteratively divide data into two homogenous, mutually exclusive groups based on a threshold in an explanatory variable while minimizing the variation (sum of squares) of the response variable within the two groups [*Breiman et al.*, 1984; *De'ath and Fabricius*, 2000; *De'ath*, 2002]. Regression trees can perform well with complex ecological data that exhibit high-order interactions, multicollinearity, and nonlinear relationships between predictor variables [*De'ath and Fabricius*, 2000; *De'ath*, 2002]. We included both in situ and satellite data for the 11 lakes that had both; and both in situ and satellite data appeared in the same leaf for each lake, improving our confidence in the resulting model. We also included a "datatype" variable that distinguished between in situ and satellite data, and this was not significant. An *n*-fold cross-validation procedure was used. The most parsimonious regression tree was selected by pruning the tree to the level where the complexity parameter minimized the cross-validation error [*Sharma et al.*, 2012]. The regression tree was pruned to a depth in which the complexity parameter minimized the cross validation error. The percent variation (R^2) explained by the regression tree was calculated as follows: $R^2 = 1 - \text{Relative Error}$ [*Sharma et al.*, 2012]. All regression trees were developed using the "rpart" package in *R* [*R Development Core Team*, 2014] and also using JMP 10 (SAS Institute, Inc.).

3. Results and Discussion

Our synthesis shows that lake summer surface water temperatures (LSSWT) are warming significantly, with a mean trend of 0.34°C decade^{-1} (95% CI: 0.16–0.52), across 235 globally distributed lakes between 1985 and 2009 (Figure 1). This warming rate is consistent with the rapid annual average increase in air temperatures (0.25°C decade^{-1}) and ocean surface temperatures (0.12°C decade^{-1}) over a similar time period (1979–2012) [*Hartmann et al.*, 2013a]. The difference between the overall trend for summer air and lake temperatures was not statistically significant across these sites, indicating broad global coherence in air and lake temperature trends. However, for individual lakes, air and lake temperature trends often diverged (Figure 2), emphasizing the importance of understanding the various factors that control lake heat budgets rather than assuming lake temperatures will respond similarly to air temperatures.

Although warming is widespread, LSSWT trends range from −0.7 to 1.3°C decade^{-1} and show clear regional variation. Previous studies that have used only satellite data, necessarily constrained by the technology to focus on larger lakes, also reported a range of warming rates, in step with or exceeding that of air temperature [*Schneider et al.*, 2009; *Layden et al.*, 2015]. Our data set allowed exploration of a range of potential drivers across a broader suite of lakes. Within our data set, no single geographic (latitude and elevation) or morphometric factor (depth, volume, and surface area) adequately explained this variation, since correlations between these geomorphic factors and LSSWT were weak (<0.2) to moderate (<0.4) (Figure S2). Warm-water

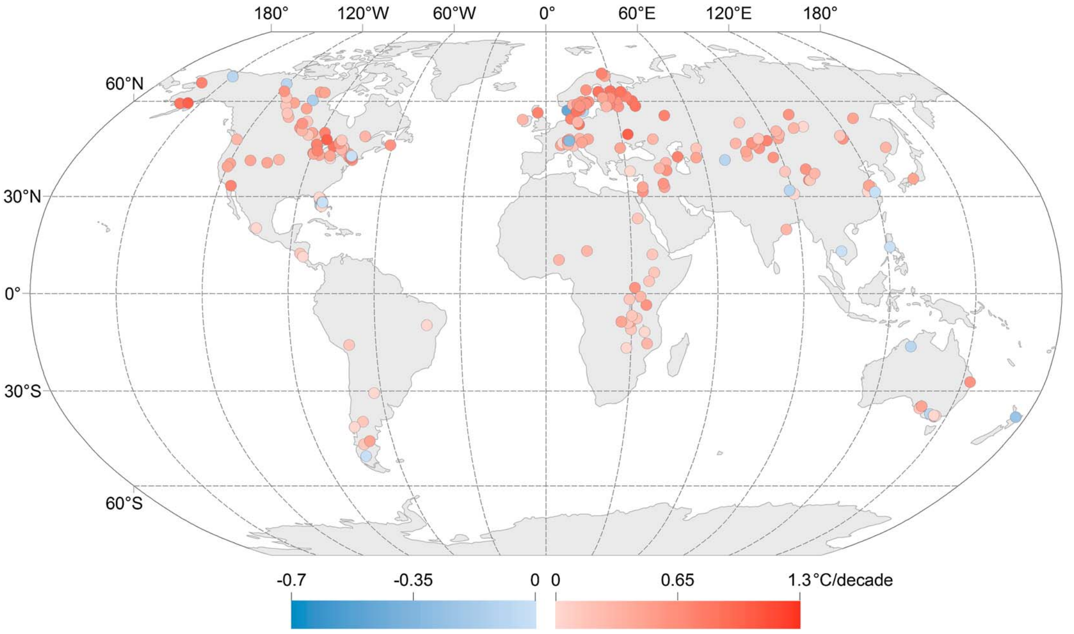

Figure 1. Map of trends in lake summer surface temperatures from 1985 to 2009. Most lakes are warming, and there is large spatial heterogeneity in lake trends. Note that the magnitudes of cooling and warming are not the same.

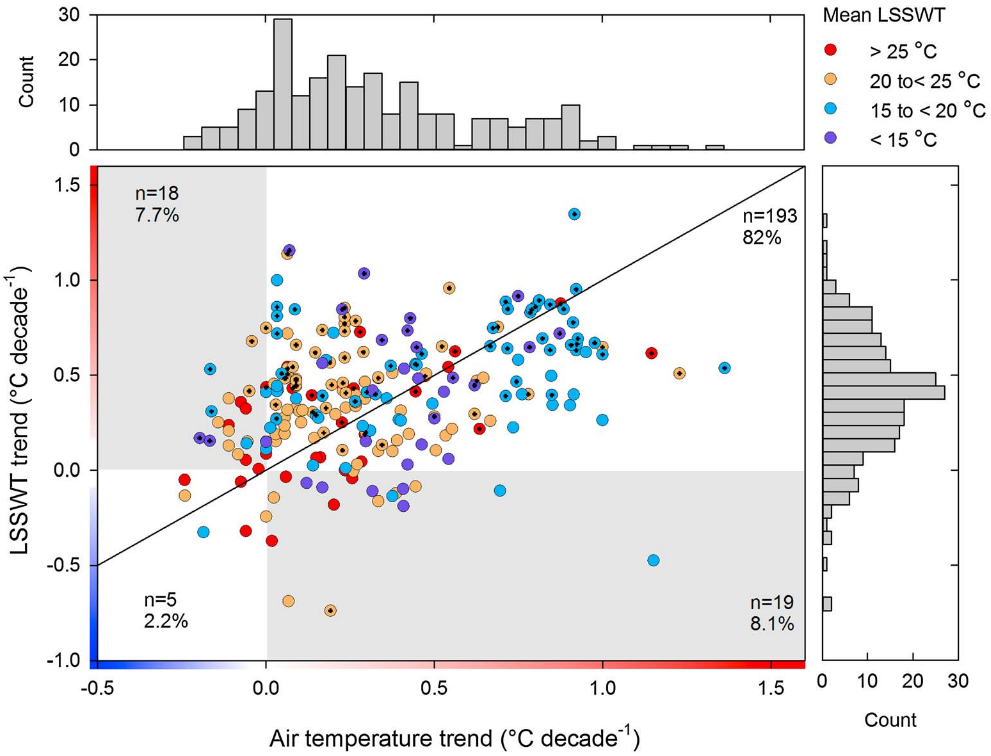

Figure 2. Lake summer surface water temperature (LSSWT) trends varied widely. Although the slope of the linear regression line between LSSWT trends and air temperature trends was not significantly different from 1, there was wide variation in both air and lake temperature trends. LSSWT trends significant at $p < 0.1$ are indicated by a black central dot within a data point. Included are the 1:1 line and counts (n) and % in each quadrant. Histograms show distribution of data along that axis.

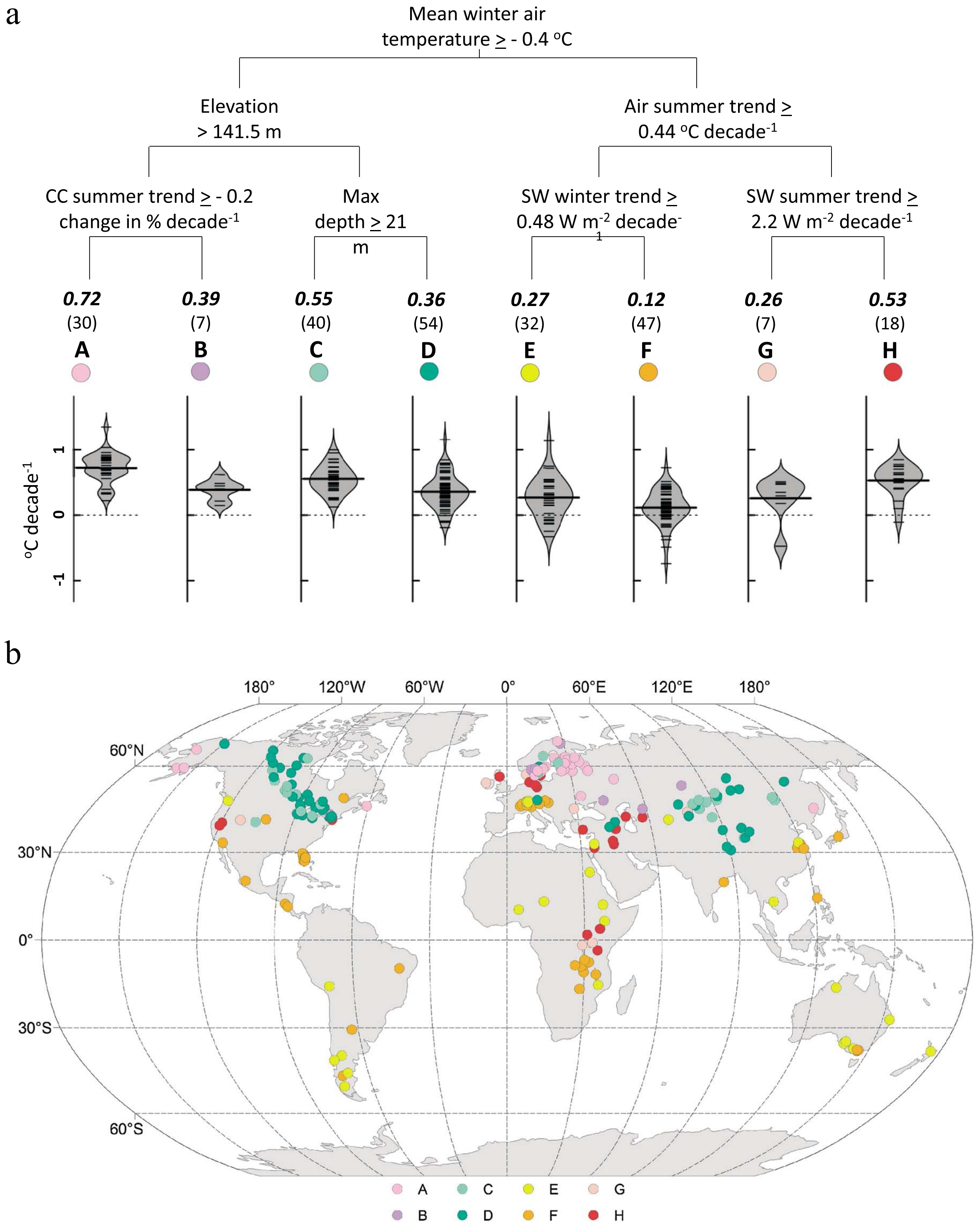

Figure 3. Groups of lakes sharing similar factors influencing LSSWT trends are not regionally clustered. (a) Regression tree of key climatic (air (degree Celsius decade^{-1}), cloud cover (CC) (change in % coverage decade^{-1}), shortwave radiation (SW) (W m^{-2} decade^{-1})), and geomorphometric characteristics influencing lake summer surface water temperature (LSSWT) trends. The inequality applies to the right side of the split. The mean LSSWT trend (degree Celsius decade^{-1}) for each leaf is given in bold at the end of each branch, with the count (*n*) in parentheses. Letters refer to rows in Table S4, where more information about each leaf is provided. Violin plots under each leaf show the mean and distribution of the lake temperature trends within the leaf. (b) Spatial representation of lakes within each regression tree leaf, showing that lakes that are warming at similar rates due to shared climatic and geomorphic characteristics are widely distributed across the globe.

and cool-water lakes showed similar ranges of warming rates (Figure 2). Furthermore, lake warming rates were heterogeneous even within regions; both warming and cooling trends occurred in high-latitude lakes (e.g., Alaska) and in nearby lakes within several regions (e.g., Central Europe and Tibetan Plateau). Proximal similarity analyses indicated that in both the Laurentian Great Lakes region and in Northern Europe, lakes were warming significantly faster than the global average (Figure S3), confirming previous findings [*Schneider and Hook*, 2010; *Hook et al.*, 2012]. In contrast, lakes in southeastern North America were warming significantly more slowly than the global average (Figure S3).

Our interannual models of LSSWT indicate good predictions of LSSWT from the available climate and geomorphic factors. The multiple regression model suggests that only elevation and winter shortwave radiation were not significant predictors of LSSWT and aggregate predictive power was high (multiple regression: $R^2 = 0.82$, RMSE = 0.42°C, Table S3). Even without taking into account factors such as wind, relative humidity, water transparency, and residence time, the model explained as much variation as interannual studies that have included additional variables [*Sharma et al.*, 2008]. The mixed effect and year-specific multiple regressions provide further evidence that our predictor set is appropriate and powerful, and all three statistical approaches point to summer air temperature as the single most important and consistent predictor of LSSWT (Table S3). These results underscore the fact that LSSWT is under tight physical control by climate drivers and geomorphic characteristics.

This large heterogeneity in LSSWT trends is associated with diverse climate and geomorphic factors. Major climate changes over the last few decades include increases in air temperatures [*Karl et al.*, 2015], shifts in cloud cover and type in many regions [*Eastman and Warren*, 2013], and increases or decreases in solar radiation at various locations around the globe [*Wild*, 2012]. The explanatory power of these climate variables is mediated by the morphometric properties of individual lakes that affect the efficiency of heat transfer [*Toffolon et al.*, 2014]. In our data set, % cloud cover, air temperature, and shortwave radiation are only weakly to moderately correlated (<0.4) suggesting that multicollinearity is minimal and that each of these variables should be used to model lake surface water temperatures.

Regression tree analysis implied both nonlinear effects and complex interactions among variables ($R^2 = 64\%$ for full model, $R^2 = 45\%$ for pruned model; Figure 3a). Winter ice cover appears to be a key factor influencing LSSWT trends (Figure 3a). Mean winter air temperatures of -0.4°C marked the first split in the regression tree for predicting lake temperature trends. This mean winter air temperature has previously been associated with ice formation [*Weyhenmeyer et al.*, 2004], and we found that the split accurately reflected the division between lakes in our database that become seasonally covered by ice (hereafter referred to as ice-covered lakes) versus lakes with no seasonal ice cover (ice-free lakes) (Table S4). On average, ice-covered lakes are warming significantly faster than lakes that do not experience ice cover (Wilcoxon $p < 0.0001$; ice-covered median 0.48°C decade^{-1}, 95% CI 0.45 to 0.55; warm-winter median 0.25°C decade^{-1}, 95% CI 0.19 to 0.31). Among ice-covered lakes, LSSWT trends were related to both geomorphic characteristics and cloud cover trends. In contrast, LSSWT trends in ice-free lakes were more closely associated with trends in air temperature and solar radiation.

Ice-covered lakes are typically warming faster than ambient air temperatures, and lake morphology affected the strength of this response. The world's deepest ice-covered lakes warmed twice as fast as the overlying air temperatures, consistent with previous single-lake studies (e.g., [*Austin and Colman*, 2007; *Hampton et al.*, 2008]). For these large, deep lakes, the combination of shorter ice duration [*Magnuson*, 2000] and rising air temperatures can lead to earlier summer stratification that results in surface waters warming more rapidly than air [*Austin and Colman*, 2007], whereas in smaller, shallower lakes, surface water temperatures should more closely track changes in air temperature [*Toffolon et al.*, 2014]. In addition, summer shortwave radiation trends were significantly greater for ice-covered lakes (Wilcoxon $p < 0.0001$) (Figure 3a), and the lakes exhibiting the highest warming rates also experienced substantial decreases in summer cloud cover (leaves A and C, Table S4). Thus, we infer that the highest warming rates occur in ice-covered lakes that are subject to a combination of shorter ice duration, decrease in cloud cover, and increase in both summer air temperature and shortwave radiation (Figure S4). A more detailed exploration of the interplay between these various climate drivers, by investigating the impact of temperature-related changes in ice-cover relative to increases in shortwave radiation, for example, would be beneficial for improving our ability to predict lake changes.

Ice-free lakes are warming more slowly, frequently at rates similar to or less than those of air temperature. This pattern accords with theoretical predictions based on the psychrometric properties of air and water, which dictate that long-term rates of temperature change should be lower for lakes than air [*Schmid et al.*, 2014]. Among ice-free lakes in our survey, the main exceptions were observed in Florida and Australia, where surface temperatures of multiple lakes changed faster than air temperatures (cooling in Florida and warming in Australia). Aside from certain small lakes (primarily) in Australia, the highest warming rates among ice-free lakes were cases where both summer air temperature and summer shortwave radiation increased (leaf H, Figure S4). Although 10% of lakes showed cooling trends (Figure 2), underlying reasons for cooling were apparently site specific (Table S2).

4. Conclusion

The high level of spatial heterogeneity in lake warming rates found in this study runs counter to the common assumption of general regional coherence. Lakes for which warming rates were similar in association with particular geomorphic or climatic predictors (i.e., lakes within a "leaf") showed weak geographic clustering (Figure 3b), contrary to previous inferences of regional-scale spatial coherence in lake warming trends [*Palmer et al.,* 2014; *Wagner et al.*, 2012]. In fact, similarly responding lakes were broadly distributed across the globe, indicating that lake characteristics can strongly mediate climatic effects. The heterogeneity in surface warming rates underscores the importance of considering interactions among climate and geomorphic factors that are driving lake responses and prevents simple statements about surface water trends; one cannot assume that any individual lake has warmed concurrently with air temperature, for example, or that all lakes in a region are warming similarly. Predicting future responses of lake ecosystems to climate change relies upon identifying and understanding the nature of such interactions.

Consequences of this extensive warming are numerous and diverse. The global average lake summer surface water warming rate found here implies a 20% increase in algal blooms and a 5% increase in toxic blooms over the next century [*Brookes and Carey*, 2011; *Rigosi et al.*, 2015], as well as a 4% increase in methane emissions from lakes during the next decade. Increased evaporation associated with warming can lead to declines in lake water level, with implications for water security [*Vorosmarty*, 2000; *Hanrahan et al.*, 2010], substantial economic consequences [*Gronewold and Stow*, 2014], and in some cases, complete ecosystem loss (e.g., [*Smol and Douglas*, 2007]). Already, changes in thermal structure and mixing have decreased productivity of some lakes, which threaten human communities that depend on fisheries as a nutritional and economic resource [*O'Reilly et al.*, 2003]. Lakes with high rates of surface temperature change may appear more likely to experience major ecosystem changes [*Smol et al.*, 2005; *Smol and Douglas*, 2007], but we caution that even lakes with low rates of change may be under ecosystem stress if the initial water temperatures are already near physiological maxima [*Tewksbury et al.*, 2008]. The widespread warming reported here suggests that large changes in Earth's freshwater resources and their processes are not only imminent but already under way.

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