Climate-induced warming of lakes can be either amplified or suppressed by trends in water clarity

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Abstract
Climate change is rapidly warming aquatic ecosystems including lakes and reservoirs. However, variability in lake characteristics can modulate how lakes respond to climate. Water clarity is especially important both because it influences the depth range over which heat is absorbed, and because it is changing in many lakes.

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The hydrodynamic model used, General Lake Model (GLM), is available at: http://aed.see.uwa.edu.au/research/models/GLM/ and GLM source code is available at: https://github.com/AquaticEcoDynamics/GLM.

Observational data for Crystal and Sparkling Lakes is available through the North Temperate Lakes Long Term Ecological Research site (https://lter.limnology.wisc.edu/). Specifically, we used the NTL LTER water clarity dataset (number 5730), referred to as the "North Temperate Lakes LTER: Light Extinction-Trout Lake Area 1981 - current" (available online at: https://lter.limnology.wisc.edu/data/filter/5730) and the temperature dataset (number 5731), referred to as "Physical Limnology of the North Temperate Lakes Primary Study Lakes" (available online at https://lter.limnology.wisc.edu/data/filter/5721). Light extinction coefficients (Kd, units: m−1) were converted to estimates of Secchi depth (units: m) using the relationship Kd = 1.7/Secchi depth.

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Here, we show that simulated long-term water clarity trends influence how both surface and bottom water temperatures of lakes and reservoirs respond to climate change. Clarity changes can either amplify or suppress climate-induced warming, depending on lake depth and the direction of clarity change. Using a process-based model to simulate 1894 north temperate lakes from 1979 to 2012, we show that a scenario of decreasing clarity at a conservative yet widely observed rate of 0.92% yr\(^{-1}\) warmed surface waters and cooled bottom waters at rates comparable in magnitude to climate-induced warming. For lakes deeper than 6.5 m, decreasing clarity was sufficient to fully offset the effects of climate-induced warming on median whole-lake mean temperatures. Conversely, a scenario increasing clarity at the same rate cooled surface waters and warmed bottom waters relative to baseline warming rates. Furthermore, in 43% of lakes, increasing clarity more than doubled baseline bottom temperature warming rates. Long-term empirical observations of water temperature in lakes with and without clarity trends support these simulation results. Together, these results demonstrate that water clarity trends may be as important as rising air temperatures in determining how waterbodies respond to climate change.

Climate change is warming lakes (Schneider and Hook 2010; Butcher et al. 2015; O’Reilly et al. 2015), with important implications for their ecology and the goods and services they provide to society (Woodward et al. 2010; Carpenter et al. 2011; Shimoda et al. 2011). In lakes, warming is driven primarily by rising air temperatures (Schmid et al. 2014; Toffolon et al. 2014; Butcher et al. 2015; Layden et al. 2015; O’Reilly et al. 2015). However, warming rates can vary widely among lakes (O’Reilly et al. 2015). This is in part because variability in lake characteristics can modulate how lakes respond to air temperature changes (Bayer et al. 2013; Schmid et al. 2014; Kraemer et al. 2015a, 2015b). In particular, water clarity can regulate how water bodies respond to atmospheric warming by controlling how solar radiation is absorbed in the water column (Persson and Jones 2008; Rinke et al. 2010; Read and Rose 2013). For example, single lake studies have shown that large clarity declines contribute to warmer surface waters but volumetrically cooler lakes, even during periods of rising air temperatures (Tanentzap et al. 2008; Rinke et al. 2010).

Water clarity is changing in many lakes and reservoirs, with both increasing and decreasing trends frequently reported (McCulloch et al. 2013; Olmanson et al. 2013; Lottig et al. 2014; Rose et al. in press). While large and abrupt step-changes in water clarity are possible in certain systems (Scheffer et al. 1993), long-term clarity trends with annual rates of change of about 1% are common (Lottig et al. 2014). Water clarity affects lake water temperature by influencing the vertical partitioning of heat and outward heat fluxes. For example, lakes with low water clarity trap heat closer to the surface and have larger outward heat fluxes (Read and Rose 2013). However, the temperature profiles of diverse lakes may respond differently to identical changes in clarity. Lake depth may be an important characteristic that regulates how clarity influences lake temperatures. Specifically, depth may constrain the maximum vertical difference in temperature that changes in water clarity can produce, with deeper lakes being more sensitive to clarity changes (Gorham 1964).

Until now, the role of clarity in determining lake responses to climate change has not been tested, in part due to the paucity of geographically distributed long-term water temperature and clarity records. Process-based hydrodynamic models may provide a solution to overcome this data limitation. These models are commonly applied tools to understand and predict climate change impacts on lakes when observational data are sparse (Fang and Stefan 2009; Bayer et al. 2013; Fink et al. 2014; Read et al. 2014; Schmid et al. 2014; Butcher et al. 2015). Process-based simulation models can accurately predict water temperatures for spatially distributed lakes for several reasons. First, monitoring data exist for key components of lake heat budgets (e.g., solar radiation). Second, hydrodynamic model complexity is relatively constrained (compared with biological or biogeochemical models). This approach is especially powerful when validated with long-term observational data. Additionally, new modeling approaches enable the simulation of thousands of lakes simultaneously (Read et al. 2014).

Here, we employ a scenario approach to ask if conservative long-term trends in water clarity can meaningfully influence the thermal response of a diverse and broadly representative population of lakes to climate change. We then complement scenarios with observational data demonstrating the model’s ability to simulate realistic water

### Table 1. Values used for GLM model parameters for simulation of the 1894 north temperate lakes from 1979 to 2012.

| Parameter                                      | Value     |
|------------------------------------------------|-----------|
| Minimum layer thickness (m)                    | 0.2       |
| Maximum layer thickness (m)                    | Varied; 0.3–1.5 |
| Bulk aerodynamic transport coefficients        | 0.0013    |
| Convective overturn mixing efficiency          | 0.125     |
| Wind stirring efficiency                       | 0.23      |
| Shear production efficiency                    | 0.2       |
| Kelvin–Helmholtz turbulent billows mixing efficiency | 0.3      |
| Hypolimnetic turbulence mixing efficiency      | 0.5       |
temperature trends in two neighboring lakes, one with a long-term clarity trend and one without. We predicted that increasing clarity would amplify whole-lake and bottom temperature warming, but suppress surface temperature warming. Conversely, we predicted that decreasing clarity would suppress whole-lake average and bottom temperature warming, but amplify surface temperature warming. Finally, we predicted that lake depth would regulate how sensitive lake temperatures are to changing water clarity because depth influences the maximum vertical difference in heat partitioning.

Methods

We used the process-based model General Lake Model (GLM; Hipsey et al. 2014) version 2.0.2 to model the thermal characteristics of 1894 north temperate lakes in Wisconsin, U.S.A. at a daily time-step over the period 1979–2012. Important model parameters are described in Table 1. Consistent with existing studies (e.g., O’Reilly et al. 2015), we focus on summertime (July, August, and September) temperatures. Thus, data represent summertime averages and not annual temperatures or trends.

We use GLM to explore trends in surface, bottom, and whole lake mean temperatures. GLM utilizes a vertically layered Lagrangian structure to simulate water temperatures. We defined surface and bottom temperatures as the modeled temperature of the shallowest and deepest model layer respectively. Whole-lake mean temperature refers to the volumetrically averaged temperature and was calculated in each lake using a set of 20 temperature measurements in each water column and accounting for the volume in each layer.

Heat flux model components were formatted as time-series inputs to GLM for wind speed, air temperature, relative humidity, precipitation, and downwelling longwave and shortwave radiation. Data for these model components was accessed from the North American Land Data Assimilation System (NLDAS; ldas.gsfc.nasa.gov/nldas). A statewide air temperature trend was estimated over the same period using data from the National Oceanic and Atmospheric Administration (NOAA) National Centers for Environmental Information (NCEI; https://www.ncdc.noaa.gov/climate-monitoring/).

Lake-specific model inputs included hypsographic curves (or estimates thereof), wind sheltering coefficients, and water clarity. Hypsographic curves were estimated either from bathymetric maps or a cone parameterized by lake surface area and maximum depth (Read et al. 2014). Wind sheltering coefficients were estimated from lake surface area and surrounding vegetation height (Van Den Hoek et al. 2015). Water clarity starting points for each lake (values for year 1979 and all years for the baseline simulation; see below) were derived from in situ Secchi disk depth measurements and Landsat satellite-derived Secchi disk depth estimates.

Secchi disk depths were calculated as the mean of all observations for each lake. Lakes ranged in maximum depth from 0.9 m to 106.7 m (median: 7.3 m), in area from 1 ha to 53,394 ha (median: 29 ha), and in initial Secchi disk depth from 0.1 m to 13.4 m (median: 2.5 m).

Lake simulations were not calibrated to individual lakes. Model accuracy was evaluated by root mean squared error (RMSE) for epilimnion, hypolimnion, and whole-lake mean temperature profiles. The RMSE between model simulated and observed temperatures was 2.72°C for all depths ($n = 224,812$ measurements in 1137 lakes), 1.84°C for epilimnetic temperatures ($n = 13,708$ measurements in 643 lakes), 3.26°C for hypolimnetic temperatures ($n = 13,708$ measurements in 643 lakes), and 2.07°C for whole-lake mean temperatures ($n = 23,005$ measurements in 747 lakes). For the July–August–September period, RMSE values were 0.98°C for epilimnetic temperature ($n = 188$ measurements in 54 lakes), 2.00°C for the hypolimnnetic temperature ($n = 188$ measurements in 54 lakes), and 1.87°C for whole-lake mean temperatures ($n = 188$ measurements in 54 lakes). For further details on the model performance, see Read et al. (2014). We ran three 34-yr scenario simulations for all lakes to assess the potential impacts of long-term changes in clarity on lake temperatures across a landscape of thousands of lakes. In the first baseline scenario, water clarity was held constant, and any trends in lake temperatures are due to changes in atmospheric forcing. We also created scenarios of increasing and decreasing clarity, where Secchi depth (in m) was increased or decreased by 0.92% yr$^{-1}$. Secchi disk depth was then converted to the diffuse attenuation coefficient ($k_d$, units: m$^{-1}$) using the equation $k_d = 1.7/$Secchi depth. The annual rate of clarity change in the scenarios was chosen to represent a conservative, realistic long-term trend in water clarity. This rate of change was calculated from survey of 3251 lakes spread across eight states in the central United States (Lottig et al. 2014). Specifically, the 0.92% yr$^{-1}$ represents the posterior estimate for the mean slope observed across the lake survey, analyzed using a hierarchical model of log$_e$-transformed Secchi depth as a linear function of year and allowing intercepts, slopes, and model error variances to differ among lakes. While the period of water clarity measurements differed among lakes, 99% of measurements were from the 1970s and afterwards. In our scenario simulations, final (year 2012) Secchi disk depths ranged from 0.2 m to 17.3 m (median: 3.2 m) for the increasing clarity scenario and ranged from 0.1 m to 9.4 m (median: 1.8 m) for the decreasing clarity scenario.

We used the Theil-Sen slope estimator (Sen 1968) to quantify annual temporal changes in lake thermal characteristics for the three scenarios. This non-parametric method calculates slopes from all permutations of paired observations, and is robust to outliers and non-normality (Wilcox 2011). We report the Theil-Sen slopes for the population of lakes as the difference between the increasing or decreasing scenario value and the baseline scenario value in order to control for long-
term trends in water temperature that were not due to chang-
ing water clarity (i.e., those due to climate warming). We also
report median Theil-Sen slopes for the baseline scenario to
assess how modeled lake temperature characteristics changed
over the period 1979–2012. A locally weighted polynomial
regression (LOWESS; a component of the R “stats” package)
was applied to each plot of Theil-Sen slopes vs. depth to visu-
alize how slopes varied for each treatment across the popula-
ton of lakes. Calculations were all run in R, version 3.2.2 (R
Core Team 2015).

In addition to our scenarios modeling thousands of lakes,
empirical observations of water temperature and clarity from
two adjacent lakes in the NTL LTER site were used as a case
study to assess if GLM accurately predicts observed tempera-
ture trends in lakes with and without clarity trends. The NTL
LTER sampling program has collected data on seven lakes in
Northern Wisconsin regularly since 1981 (https://lter.limnol-
ogy.wisc.edu/). Two of these lakes, Crystal (latitude: 46.001,
longitude: -89.614) and Sparkling (latitude: 46.005, longi-
tude: -89.699) are located 6.6 km from each other and have
similar maximum depth (20.4 m and 20.0 m, respectively),
area (37 ha and 64 ha, respectively), and Secchi depth (long
term mean of 10.3 m and 8.2 m, respectively). Crystal Lake
has experienced a long-term decline in water clarity while
Sparkling has not. At the same time, both lakes have been
exposed to a regionally warming climate. We used these lakes
as a natural experimental (Crystal) and control (Sparkling) to
assess the impacts of water clarity loss and atmospheric forc-
ing on lake temperature characteristics. We assessed changes
in observed mean summer (July, August, September) near-
surface, near-bottom, and whole-lake mean temperatures in
both lakes over the period 1981–2011 [2012 was excluded
because a whole-lake temperature manipulation experiment
began in Crystal Lake starting in 2012 (Lawson et al. 2015)].
Near-surface was defined as measurements < 0.5 m deep and
near-bottom was defined as measurements > 16 m deep in
both lakes. We also calibrated GLM to these lakes and used
site-specific lake water clarity data to test if GLM could accu-
rately predict water temperatures and temperature trends in
these lakes. Site-specific calibrations are described in the Sup-
porting Information.

Results

Lake thermal responses to clarity changes were heteroge-
eous across systems as well as within the water column of
individual systems (Fig. 1). Whole-lake mean summer tem-
peratures increased by a median of 0.237°C decade⁻¹ under
the baseline scenario, meaning that lakes warmed by a
median of about 0.8°C over the 34 yr period absent of
changes in water clarity (Table 2). Surface and bottom tem-
peratures warmed at median rates of 0.267 and 0.216°C deca-
de⁻¹, respectively, under the baseline warming rate. Inclusive of baseline warming, over the 34-yr study
period this translates to a median increase in surface

Fig. 1. Trends in surface (A), bottom (B), and whole-lake (C) mean temperature for simulations in increasing (blue), and decreasing (brown) clarity.

Table 2. Estimated median trends (units: °C decade⁻¹) for 1894 lakes simulations of increasing or decreasing water clarity at 0.92% yr⁻¹ and no trend in water clarity.

| Scenario                              | Surface   | Bottom    | Whole lake average |
|---------------------------------------|-----------|-----------|-------------------|
| Increasing water clarity              | 0.222 (0.8) | 0.303 (1.0) | 0.263 (0.9)       |
| Decreasing water clarity              | 0.316 (1.1) | 0.097 (0.3) | 0.155 (0.5)       |
| No change in water clarity (baseline) | 0.267 (0.9) | 0.216 (0.7) | 0.237 (0.8)       |

Values in parentheses indicate the temperature change (units: °C) over the 34 yr simulation period, 1979–2012.
temperature of 1.1°C, and a much smaller median increase in bottom temperature of 0.3°C in lakes with decreasing clarity (Table 2). In 48% of lakes, declining water clarity more than fully offset the effects of climate warming, and lake bottom waters actually cooled over the study period in spite of climate warming. Increasing clarity had opposite effects. Increasing clarity by 0.92% annually suppressed the median surface warming rate by 17%, and accelerated the median bottom temperature warming rate by 41% relative to the baseline. Inclusive of baseline warming, over the 34-yr study period, median surface temperatures increased by 0.8°C and bottom temperatures increased by 1.0°C in lakes with increasing clarity (Table 2). In 43% of lakes, increasing clarity more than doubled baseline bottom temperature warming rates.

Because of the opposite effects of water clarity changes on surface and bottom waters, clarity changes often influenced mean whole-lake temperatures less so than they did bottom waters alone. Furthermore, whole-lake temperatures frequently moved in the opposite direction compared with surface water temperatures. In 26% of lakes, decreasing clarity more than fully suppressed whole-lake warming, and whole-lake temperatures actually cooled as lakes became less clear despite warming in the baseline scenario. Across all lakes, increasing clarity...
accelerated the median whole-lake warming rate by 11%, while decreasing clarity suppressed the median warming rate by 35% (relative to the baseline). Inclusive of baseline warming, whole-lake temperature increased by a median of 0.9°C in response to increasing clarity, nearly double the increase (0.5°C) seen in lakes undergoing decreasing clarity (Table 2).

Water bodies responded to clarity changes quite differently from one another, highlighting the importance of site-specific features in regulating lake thermal responses to climate. In particular, bottom temperature responses to clarity changes varied substantially among lakes. For example, while decreasing clarity accelerated the surface temperature warming rate in over 99% of lakes, it suppressed baseline bottom temperature warming in 78% of lakes and amplified bottom temperature warming in 22%. Similar to lake bottom temperatures, whole-lake temperature responses to changing clarity were quite variable. Decreasing water clarity suppressed baseline whole-lake warming in 65% of lakes, while it accelerated warming in 35%.

Maximum depth strongly influenced lake thermal sensitivity to clarity changes (Fig. 3). Whole-lake temperatures of deep lakes were particularly sensitive to clarity changes. For example, for lakes >6.5 m deep, decreasing clarity actually reduced the median whole-lake temperature for this subset of lakes despite substantial warming under the baseline scenario. The median baseline warming rate for this population of lakes (n = 1061) was 0.251°C decade⁻¹, which is slightly higher than the total lake population (0.237°C decade⁻¹). In contrast, bottom temperatures in lakes of intermediate depth (3–18 m) were particularly sensitive to clarity changes (Fig. 3). Decreasing clarity in lakes of this depth range was sufficient to cool lake bottom waters despite baseline warming, while increasing clarity more than doubled bottom temperature warming relative to the baseline rate. Shallow lakes (<3 m) were relatively insensitive to clarity trends (Fig. 3).

Long term in situ measurements of water clarity and temperature at two North Temperate Lakes Long Term Ecological Research sites, Crystal and Sparkling Lakes, support simulation results showing that declining clarity suppresses warming and can even lead to cooling trends despite regional warming (Fig. 4). Over the period 1981–2011, water clarity in Sparkling Lake did not change significantly (p = 0.157), while water clarity decreased significantly by 2.2% yr⁻¹ in Crystal Lake (p < 0.001). Summertime surface and bottom water temperatures in Sparkling Lake increased by 0.421°C decade⁻¹ (p = 0.035) and 0.234°C decade⁻¹ (p = 0.036), respectively. Relative to Sparkling Lake, decreasing water clarity accelerated warming in the surface waters of Crystal Lake by a rate of 0.494°C decade⁻¹ (17%; p = 0.042), while also substantial cooling bottom waters (rate of −0.517°C decade⁻¹, p = 0.043). When calibrated to Crystal and Sparkling Lakes, model predictions matched observed data and trends well (Table 3). In both lakes, RMSE was higher for bottom water temperatures than for surface or whole lake average.

Table 3. Observed and simulated trends in water temperature (units: °C decade⁻¹) in Crystal and Sparkling Lakes over the period 1982–2011.

|          | Surface | Bottom | Whole lake average |
|----------|---------|--------|--------------------|
| Crystal  | Observed trend | 0.58 (1.8) | −0.44 (1.4) | 0.24 (0.7) |
|          | Modeled trend | 0.56 (1.7) | −0.30 (0.9) | 0.23 (0.7) |
|          | RMSE     | 0.43    | 0.76              | 0.57      |
| Sparkling| Observed trend | 0.55 (1.7) | 0.46 (1.4) | 0.69 (2.1) |
|          | Modeled trend | 0.43 (1.3) | 0.3 (0.9) | 0.54 (1.7) |
|          | RMSE     | 0.57    | 0.80              | 0.78      |

Values in parentheses indicate the temperature change (units: °C) over the 31 yr simulation period, 1981–2011. RMSE refers to root mean squared error (units: °C).
temperature, but lower than the observed change in temperature over the simulation period.

Discussion

Our results show that trends in water clarity can substantially influence the thermal trajectories of lakes and reservoirs, especially in systems more than a few meters deep. Studies of climate change impacts on lakes and reservoirs have primarily focused on large, deep lakes (Schneider and Hook 2010; Shimoda et al. 2011; Fink et al. 2014; Layden et al. 2015; but see O’Reilly et al. 2015). Many lakes in which warming trends have been documented also have experienced long-term changes in water clarity (Shimoda et al. 2011). For example, Lake Tanganyika, located in the African Rift Valley, has experienced a long-term increase in water clarity equivalent to 1.1% yr⁻¹ over the period 1913–1996 (Verburg et al. 2003) and an increase in surface temperature of 0.129°C decade⁻¹ over the period 1912–2013 (Kraemer et al. 2015a, 2015b). Consistent with an effect of increasing clarity, deeper waters (50–80 m) have warmed faster than surface waters (Kraemer et al. 2015a, 2015b). In this case, the surface temperature may have warmed faster and deeper waters more slowly than they would have if water clarity had not increased.

Because changing water clarity influences the vertical partitioning of heat, the magnitude of clarity changes on temperature depended in part on lake depth (Fig. 3). Bottom temperatures of deep lakes were relatively insensitive to clarity changes because they received little solar radiation even when clarity was high, and therefore trends in water clarity produced only small changes in temperature. Meanwhile, shallow lakes (< 3 m) were relatively insensitive to clarity trends because they mixed more frequently than deeper lakes. For example, the median duration of stratification was about 40% shorter in lakes < 3 m deep than it was in lakes > 3 m deep. The combination of these two factors explains why lakes of intermediate depth (3–18 m) were particularly sensitive to clarity changes.

Increasing water clarity can have the same direction and magnitude of effect on whole-lake warming as climate-induced summertime warming of lakes. Given that water clarity is frequently used as a metric of water quality and clarity targets are used as management objectives, efforts to improve water clarity may have the unintended consequence of accelerating whole-lake warming rates. This effect may explain why lakes are warming faster than the atmosphere in some regions (Austin and Colman 2007; O’Reilly et al. 2015). For example, realoligotrophication of the large Central European Lake Constance has resulted in warmer temperatures at 7.5–10 m depth, even after correcting for changes in air temperature forcing (Rinke et al. 2010).

The scenario results are complemented by our two case study lakes, where our model accurately simulated observed changes in water temperatures resulting from the combined influence of climate change and clarity change. When calibrated to Crystal and Sparkling individually, model error rates (RMSE) were lower than the observed change in temperature. In contrast, in other studies simulating water temperatures model RMSE can exceed observed temperature change even when a model is calibrated to an individual lake (Bennington et al. 2010). However, it should be noted that RMSE values can vary with the time scale over which values are calculated (Piccolroaz et al. in press). Additional confidence in the model performance’s comes from the fact that the modeled baseline warming rates are consistent with estimates of the warming rates in lakes relative to the atmosphere (70–85%; Schmid et al. 2014). When paired with observational data, simulation models serve as an important tool to assess interactions among lake characteristics and future trends in lake temperature and to characterize trends across large numbers of lakes where observational data are unavailable.

Several factors may contribute to uncertainty in model predictions. A generic calibration was applied to all lakes, but some parameterizations, such as those describing energy and momentum fluxes, may vary based on lake-specific features. This was dealt with by using site-specific data (e.g., wind sheltering; Van Den Hoek et al. 2015) when possible. However, a previous analysis of simulation results using lakes in this study has shown that lake-specific RMSE was significantly correlated with features such as lake depth and water clarity, while lake-specific RMSE was uncorrelated with features such as lake area and surrounding canopy height (Read et al. 2014). Here, lake depth explained variability in lake temperature sensitivity to changing water clarity (Fig. 3). Deep lakes are especially sensitive to parameterizations of water clarity, and less sensitive to parameterizations of other characteristics such as wind-sheltering (Read et al. 2014). The initial parameterization of water clarity suffers from the fact that water clarity estimates were unavailable for every lake in every year. Furthermore, water clarity can vary seasonally (Morris and Hargreaves 1997; Lathrop et al. 1999), which was unaccounted for in the model and may have contributed to the relatively large RMSE in bottom temperature measurements and in deeper lakes. Improvements in the ability to evaluate water clarity at both intra- and inter-annual scales should improve the accuracy of hydrodynamic models with improvements most noticeable in deep lakes.

We simulated a relatively conservative rate of change in water clarity, 0.92% yr⁻¹. This rate represents a mean estimate observed across a survey of thousands of lakes and reservoirs throughout eight states in the north-central United States (Lottig et al. 2014). However, faster rates are certainly plausible. For example, Crystal Lake has experienced a 2.2% yr⁻¹ decline in water clarity over the period 1981–2011 (Fig. 4a). Faster clarity changes will have the effect of altering temperatures at faster rates, and permanent water clarity changes will also permanently alter thermal characteristics.
While our scenarios simulated identical rates and direction of change in all 1894 lakes, it is unlikely that water clarity in all lakes in a region will change simultaneously. One recent study found that 29% of Wisconsin lakes have exhibited trends in water clarity, with the vast majority (23% of all lakes) declining in clarity (Rose et al. in press). Agricultural land use intensification and increasing precipitation were attributed as the primary drivers of water clarity loss. In other regions, changes in dissolved organic matter play an important role in water clarity trends (Morris et al. 1995; Schindler et al. 1997). Thus, observed trends in water clarity may increase or decrease depending in large part on future changes in land management practices, acid deposition, and precipitation (Monteith et al. 2007; Carpenter et al. 2015). Studies that include other regions have found that about 10% of lakes have long term trends in water clarity (Olmanson et al. 2013; Lottig et al. 2014). Interestingly, a recent global analysis found that a small minority of lakes (about 10%, but only one trend significant) have exhibited cooling trends (O’Reilly et al. 2015). Changing clarity may be a factor contributing to the observed cooling trends in many of these lakes.

Because water clarity can accelerate or suppress water temperature trends, clarity may also regulate how aquatic taxa experience climate changes. In particular, the bottom waters of deep lakes with declining clarity may provide a refuge from climate-induced warming for thermally sensitive aquatic organisms. However, this thermal-maintenance comes with tradeoffs. Declining clarity may increase the risk of hypoxia and decrease primary productivity supporting higher trophic levels (Verburg et al. 2003) and reduce the efficiency of visually foraging fish (Diehl 1988).

The effects of climate change on lake and reservoirs depend on both climate drivers and in-lake characteristics such as water clarity. Real-world interactions between clarity and climate change on lake temperatures are complicated by the fact that climate change alters not only air temperatures but also the amount, timing, frequency, and type of precipitation (Karl et al. 2009; Bayer et al. 2013). In many regions, extreme precipitation events are increasing (Karl et al. 2009), which can rapidly flush materials from watersheds, reducing water clarity in receiving water bodies. Watershed land cover and land use practices, particularly agriculture, are also an important control on water clarity trends (Olmanson et al. 2013). Therefore, feedbacks between land use/land cover and the effects of increasing air temperatures and changing precipitation patterns may ultimately regulate the direction and magnitude of warming of lakes and reservoirs. Our results highlight the importance of clarity trends in controlling temperatures in northern temperate lakes and the diversity of responses to the interaction of clarity and climate both across and within lakes. Understanding the implications of the range of future lake temperature warming rates among water bodies represents an important future challenge.

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