IDENTIFYING TRENDS IN DIFFERENCES BETWEEN INLAND LAKE SURFACE WATER AND SURROUNDING LAND TEMPERATURE USING A BAYESIAN FRAMEWORK

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Lake ecosystems are important to humans but also act as sentinels of climate change. Due to contact with the atmosphere and surrounding watershed, lake surface water temperature in particular reflects even small changes changes in climate. Studies have found that remote sensing observations of radiation emitted from the Earth's surface collected by satellites can be used to calculate surface water temperatures, increasing long-term climate study feasibility and potential. However, there are still few studies using remote sensing data to examine trends in surface temperatures or that relate surface temperatures with each other. Temperature is a controlling variable for many biological processes, thus shifts in temperature can result in ecological change. Further, understanding the relationship between terrestrial and aquatic temporal temperature trends within watersheds and across regions in relation to shrinking or growing lakes may reveal the direct (e.g., human manipulation) or indirect (e.g., climate) drivers of change in lake extent. Here we used Moderate Resolution Imaging Spectroradiometer (MODIS) land surface temperature (LST) product from the Aqua satellite from June 2002 to May 2018 to determine the lake characteristics that explain trends in differences between lake surface water temperature and surrounding land temperature for 95 of the largest lakes in the United States. We used a linear Bayesian regression model to estimate trend differences between surrounding land and surface water temperatures. Of the 12 most certain trend difference estimates, Lake Hartwell had the smallest difference between land and water warming trends (with water warming at a faster rate than land) and Iliamna Lake had the largest difference between land and water warming trends (with land warming at a faster rate than water).We further identified lake type (i.e. human-made or natural) and change in lake surface area (i.e. shrinking, growing, neutral, or dynamic) as significant predictors of change in temperature differences between surrounding land and surface water temperature. This analysis suggests that combined terrestrial and aquatic remote sensing could be used to identify lakes undergoing water loss or other environmental challenges across a broad spatial scale.

Introduction

Lakes play an important role in the environment, supporting biodiversity for a wide range of species and contributing to nutrient and hydrological cycles. As lakes contain a majority of available freshwater on Earth, humans also depend on lakes for drinking and irrigation water, transportation, food, and as energy sources (Dörnhöfer and Oppelt 2016). While lakes are important for environmental functions, they also are important indicators of anthropogenic environmental changes. In particular, lakes are sentinels of climate change because they are sensitive to changes in the environment, including the land and air surrounding them. Studies reviewed by Adrian et al. (2009) have concluded that lakes serve as sentinels for climate changes because they are well-defined, reflect climate changes in catchment, filter out random and short-term variability by integrating responses over time, and are globally present in different geographic locations. Among the many indicators of climate change lakes provide, water surface temperature is of particular interest. Even small changes in lake water surface temperature have profound effects on lake processes since the surface layer of lakes interacts with the surrounding atmosphere and is where most biological production occurs (O'Reilly et al. 2015). Factors such as lake depth, surface area, and volume determine the heat capacity and maximum temperature of a lake (Kalff 2002). Since inland lakes have a relatively high heat capacity, their temperatures have less short-term variability, making lake temperature an important indicator of climate change for long-term studies (Torbick et al. 2016). Studies summarized by Reinart and Reinhold (2007) show that surface temperature reflects changes in local and regional air temperatures over time, which is useful in studying effects of climate change. Therefore studying land surface water temperature (LSWT) is crucial to studying climate change.

Collecting *in situ* data from lakes or land across a broad geographic extend and over a long period of time can be difficult due to lake location and resources available to monitor them, thus remote sensing has become increasingly favorable for observing changes over time and space. Remote sensing is the science of collecting data without being in direct contact with the object. Among different remote sensing observations, satellite remote sensing is very popular for variety of environmental applications. Sensors on satellites measure the amount of radiation reflected from Earth's surface. Different wavelengths of radiation can provide different information about surfaces. For example, infrared waves are used to measure heat emission, which can provide surface temperatures for land and water (Dörnhöfer and Oppelt 2016). As of 2017, there are approximately 600 satellites for Earth observations containing different instruments launched at varying points in time that collect measurements at different intervals (Lavender 2017). Some of these satellites have data available online for public use and easy access. The Aqua satellite, launched in 1999, contains the MODIS instrument that collects measurements twice a day, making it a desirable satellite to use for examining high temporal resolution trends despite its coarse spatial resolution of 1 km (Kwok 2018). Extracting information from satellite image pixels is laborious, or may not be the goal of a study. Many agencies have developed products based on raw remote sensing data for scientists to use instead. There are algorithms that have been developed to relate remote sensing data to abiotic or biotic processes for land, ocean, and the atmosphere, but there are currently not many products designed for inland water data. This may be, in part, because (as noted above) satellite spatial resolutions range from 1 m to 25 km, or their sparse acquisition times (ranging from minutes to months). Thus more work needs to be done with remote sensing data and inland lakes to advance the field and make large-scale in-land freshwater studies more feasible.

Remote sensing data are more comprehensive than *in situ* data because data can be collected for the entire globe. Thus estimating land and lake surface water temperature change with remote sensing data allows scientists to easily compare trends in light of climate change on a larger scale. Despite the lack of inland products, studies have shown that remote sensing skin temperatures for inland lakes can be used as a proxy for LSWT (Torbick et al. 2016; Grim et al. 2013; Reinart and Reinhold 2008; Oesch et al. 2005; Sharma et al. 2015). Grim et al. (2013) used thermal infrared channels of MODIS images to construct skin temperatures using an 8 step methodology, which accurately reflected the measured *in situ* temperature oscillations and values. Torbick et al. (2016) used thermal infrared channels of Landsat to construct skin temperatures for 3955 lakes from 1984 to 2014. Over the 30 year time frame, Torbick et al. (2016) was able to analyze LSWT trends and found that lakes were warming on average. However, while air, land, and ocean temperature trends are beginning to be documented using remote sensing data (O'Reilly et al. 2015), we are unaware of any study that examines both adjacent land and inland water trends.

Being able to analyze temperature trends allows scientists to identify drivers of those trends. Since lakes vary in size and shape, temperature patterns should also vary spatiotemporally. O'Reily et al. (2015) found that a combination of geographic location, depth, volume, and surface area explained the variation in temperature trends across the globe. The spatial heterogeneity that this study found suggests that lake warming trends depend not only on geographic location, but mostly on lake characteristics. In another study, Woolway et al. (2018) analyzed 20 years of remotely sensed LSWT data from global lakes and concluded that lake morphometry specifically explains spatial variations in lake warming trends. Deeper areas of the lake were found to have increased warming trends as opposed to shallower parts of the lake, contrary to current understandings of lake warming (Woolway et al. 2018). Along with identifying drivers of temperature trends, analyzing global lake data is important for understanding the relationship between lake temperatures and other temperatures, such as air temperatures. This difference affects the atmospheric boundary layer between the lake surface and atmosphere, which in turn impact gas transfer between lakes and the atmosphere. Woolway et al. (2017) analyzed temperature differences between the air above lakes and the LSWT of 39 lakes across the globe and found that lake characteristics and geographic location also affect atmospheric boundary layer stability,which is determined by differences between air temperature and LSWT (Woolway et al. 2017).

This study used remote sensing data to compare LSWT with surrounding land temperatures. Presently, many lakes around the globe are shrinking as a result of climate change and human activities. For example, Lake Poopó has been shrinking due to climate change, drought, water diversion for agriculture, and mining (Weiss 2018). To build on using remotely sensed lake skin temperatures as a proxy for LSWT and identifying factors that cause lakes to be vulnerable to temperature changes, this study focused on addressing the question: what factors make lakes vulnerable to differences in trends between LSWT and surrounding land temperature? As shown in Woolway et al. (2017), studies have compared LSWT and air temperatures, but no study has compared LSWT to the surface temperatures of the surrounding land temperatures of the lake. By comparing the trend in the temperature difference between LSWT and surrounding land, we were able to determine if LSWT and surrounding land temperatures had similar or different trends in water temperature from 2002 to 2018. Remote sensing has become increasingly popular for analyzing land and ocean surfaces, but using remote sensing data to analyze changes of inland lakes can advance the field. Based on previous studies identifying drivers of inland lake temperature changes, we hypothesized that adjacent land use or land cover (LULC), lake depth, surface area, latitude and longitude, precipitation, elevation, and lake type may contribute to temperature changes in lakes from local and climate factors.

Methods and Materials

We analyzed 95 lakes in the United States with surface areas larger than 100 km^2 (Fig. 1). For each lake, we obtained skin temperatures and surrounding land temperatures from the MODIS instrument on the Aqua satellite. The surrounding land area was defined as the land surrounding the lake with an area that is nine times the surface area of the lake (Fig. 2). MODIS Aqua provides daily measurements taken at 1:30 AM and 1:30 PM from June 2002 to May 2018. We used the maximum daily temperature for each day (1:30 PM). We used temperature measurements processed from MODIS images by students at the City University of New York (CUNY), New York City College of Technology. The students used the MODIS MYD11A1 product. For each lake temperature, CUNY students used an average of all the lake pixels to calculate the LSWT per day. For the surrounding land temperature calculations, water bodies that were part of the defined land area were removed, and CUNY students used an average of all the remaining land pixels to calculate the surrounding land temperature. Note that the thermal bands of remote sensing satellites provide lake skin temperature, which is different than LSWT. Lake skin temperature is the temperature of the top of the water surface, whereas LSWT is the temperature of the water from the water surface to a few meters below the water surface.

For each lake, we estimated the net temperature change between surrounding land and lake surface water using a Bayesian linear model. Bayesian statistics is an area of statistics that aims to use prior information and probabilities to estimate unknown parameters. To do so, the Bayes equation,

$$P(\theta|Y) = \frac{P(Y|\theta)P(\theta)}{P(Y)}, \tag{1}$$

which can also be written as a proportionality,

$$P(\theta|Y) \propto P(Y|\theta)P(\theta), \tag{2}$$

provides a probability distribution for sampling to estimate those unknown parameters. Here, θ denotes the unknown parameters to estimate and Y denotes the observed data. In equation 1, $P(\theta|Y)$ is referred to as the posterior distribution, which is the probability the parameters are correct in light of the observed data. $P(Y|\theta)$ is referred to as the likelihood, which is the probability the data are correct in light of the estimated parameters. $P(\theta)$ is referred to as the prior distribution, which is the probability of the parameters imposed from prior information about the parameter restrictions. $P(Y)$ is the probability of the data, and is dropped in equation 2 for proportionality purposes. When building a Bayesian model, iterative updaters, such as Markov Chain Monte Carlo algorithm, use the Bayes equation to create the posterior distribution, which sampling algorithms can then use to sample for correct parameter estimates (Blangiardo and Cameletti 2015).

We used the Just a Gibbs Sampler (JAGS) package in R to estimate the slope, intercept, and error parameters for a linear model. We also included the month of temperature measurement as a fixed effect. The model ran for 15000 iterations and we sampled from the last 5000 for parameter estimates. The independent variable was time in days and the dependent variable was the difference between land and lake surface water temperature in degrees Kelvin. Each day within my data range fell into one of the following cases: (1) both surrounding land and lake surface water measurements were present, (2) neither surrounding land nor lake surface water measurements were present, (3) only surrounding land temperature was present, (4) only lake surface water temperature was present. In order to take the difference between the surrounding land and LSWT, we treated cases (3) and (4) the same as case (2) so that we only used the days that fell into case (1) for an even pairing of differences. Once we had the slope estimated for each lake, we used it to estimate the net temperature difference change over the 17 years. Using a Bayesian linear model was advantageous with this data set because one third of the days between the beginning and end dates did not have temperature readings, and the Markov Chain Monte Carlo component allowed us to estimate missing data for a more informative calculation of trend. Once we had the slope of the Bayesian linear model for each lake, we used that slope to estimate the net change in temperature between the first and last day in the data sets.

After calculating the net change in temperature for each lake, we used univariate Bayesian linear models to determine which of the following lake features is significant in explaining the net temperature changes for the lakes: latitude, longitude, lake surface area, type (human-made, natural), shore length, elevation, average depth, average elevation of the lake's watershed, area of barren land in the lake's watershed, area of cultivated land in the lake's watershed, area of developed land in the lake's watershed, area of forest land in the lake's watershed, area of water bodies in the lake's watershed, area of shrub and herbaceous land in the lake's watershed, area of wetlands in the lake's watershed, and changing surface area status (shrinking, growing, neutral, dynamic). We created this last lake feature based on the annual surface area of the lakes during the time frame of the data using annual MODIS land cover product (MOD44W). Lakes that were consistently shrinking or growing during the 17 years were respectively classified in the shrinking or growing category. Lakes that did not change surface area were classified in the neutral category. Lakes that both shrank and grew during the 17 years were classified in the dynamic category to capture the variability in their surface areas. Once we identified which lake features were significant, we included them in a final Bayesian linear model to determine their effect sizes. The final model ran for 20000 iterations, and we sampled from the last 2000. All parameters converged after 18000 iterations, determined from Gelman Rubin diagnostic plots.

Results

We built the Bayesian linear model,

$$\begin{aligned} temperature_i = {} & b_1 + b_2(day_i) + b_3(February_i) + b_4(March_i) + b_5(April_i) + b_6(May_i) + b_7(June_i) + \\ & b_8(July_i) + b_9(August_i) + b_{10}(September_i) + b_{11}(October_i) + b_{12}(November_i) + \\ & b_{13}(December_i) + error_i, \end{aligned}$$

for each of the 95 lakes, where i indicates the day and b_1 to $b_1$3 are the estimated parameters. The net temperature changes between land and water over the 17 years of data ranged from -1.26 °C to 1.06 °C. Using 95% credible intervals, we found 12 lakes (Lake Hartwell, Sam Rayburn Reservoir, Lake Clark, Iliamna Lake, Fort Peck Lake, Eufaula Lake, Wheeler Lake, Table Rock Lake, Grenada Lake, Selawik Lake, Lake Mattamuskeet, and Seneca Lake) to have net temperature changes significantly different from 0, meaning 0 is not contained in the credible interval (Fig. 3). Note that Lake Hartwell had the smallest difference between land and water temperature rates, and Lake Iliamna had the largest difference between land and water temperature rates (Fig. 4, 5). The residuals for each of the 95 models were uncorrelated, and each parameter converged by 10000 iterations (Fig. 6).

Of the 16 Bayesian univariate linear models previously described, we found type and changing surface area status to be significantly related to the net temperature change between land and water. Using type and changing surface area status, we built the final Bayesian linear model,

$$\Delta temperature_i = 0.21(Type_i) + 0.31(Growing_i) - 0.01(Neutral_i) - 0.24(Shrinking_i) - 0.15 + error_i, \quad (3)$$

where i indicates the lake, *Type* is a binary categorical variable (human-made or natural), and *Shrinking*, *Growing*, and *Neutral* are dummy variables for changing surface area status. The residuals were uncorrelated, and each parameter converged by 18000 iterations (Fig. 7).

Changing surface area status showed patterns with the net change in temperature between land and water. The interquartile range of the net change in temperature for shrinking lakes is negative. The interquartile range of the net change in temperature for growing lakes is more spread but greater than shrinking lakes. The interquartile range of the net change in temperature for neutral lakes is close to zero. The interquartile range of the net change in temperature for dynamic lakes is both negative and positive, capturing the variability of the category (Fig. 8).

When comparing type and changing surface area status, the majority of human-made lakes are either in the growing or neutral category, whereas the majority of natural lakes are either in the shrinking or dynamic category (Fig. 9).

Discussion

The sign of the net change in temperature between surrounding land and lake surface water calculated for each lake indicates whether water or land is warming faster than the other. As seen in figure 5 if the net change in temperature for a particular lake is positive, then the Bayesian linear model estimated that the land surrounding that lake is warming faster than that lake's surface water. As seen in figure 4 if the net change in temperature for a particular lake is negative, then that lake's surface water is warming faster than the land surrounding that lake. This does not imply that the land temperature is warmer than the water temperature or that the water temperature is warmer than the land temperature; it is only a measure of the rate of temperature change relative to water and land. For example, Lake Iliamna had a net change in temperature of 0.53, as seen in figure 3. Since this value is positive, the land temperature was warming faster than the water temperature for Lake Iliamna.

In figure 3, the 12 (green) that are significantly different from 0 indicate that the land and water temperature trends for those 12 lakes do not have similar rates. The 83 (tan) lakes that have net changes in temperature that are not significantly different from 0 can be broken into 2 categories. The first is represented by the black brackets in figure 3. These have larger absolute values, so their credible intervals are much wider in order to contain 0 as well as the estimated net change value. We are less certain of the estimated net changes in temperature for the lakes in this category due variability in the data. The second category is represented by the orange brackets in figure3. These have smaller absolute values and do contain 0 in their credible intervals. Thus it is possible that net change in temperature for these lakes is 0 since their credible interval is narrower around 0. Future work is needed to pinpoint which lakes in the second category have a net change in temperature of 0 and to determine with more certainty the net changes in temperature for the lakes in the first category.

The final Bayesian linear model given in equation 3 indicates that lake type (human-made or natural) and changing surface area status contribute similarly in effect size to predicting net change in temperature. Since lake type is a significant predictor of net change in temperature, it is worth noting studies that have found differences between them. Human-made and natural lakes differ in water source, bathymetry, management, and geographic distribution (Hayes et al. 2017). Lake types also differ in chemical and biological content. For example, total phosphorous levels have been found to be different between natural and human-made lakes since human-made lakes tend to have higher flushing rates and larger inputs of sediments containing phosphorous due to human activity (Canfield 1979). Studies have also found differences in trophic structures of phytoplankton between natural and human-made lakes, hypothesized to be a result of regulatory regimes humans impose on human-made lakes, such as reservoirs (Naselli-Flores and Barone 2000). Since human-made lakes and natural lakes differ in characteristics, lake type is considered in lakes and climate change studies (Hayes et al. 2017). Thus it is understandable that we found lake type in this study to be a significant predictor of net change in temperature between surrounding land and lake surface water. Future studies could further investigate the relationship between lake type and net change in temperature, determining whether human management of lakes has an effect on the surrounding land and lake surface water trends.

When isolating lake type and changing surface area status from the final Bayesian linear model, a suggestive pattern emerges from the changing surface area status variable, as seen in figure 8. Most of the shrinking lakes are negative, which indicates that the water is warming faster than the land temperature for those lakes. This suggests that shrinking lakes with faster warming water temperatures are more susceptible to water loss, whereas the growing lakes with faster warming land temperatures are less susceptible to water loss. This suggests that net change in temperature could be used to predict if lakes are vulnerable to shrinking or growing. As lakes are shrinking and growing around the world, the shrinking lakes are of particular concern given humans and the environment rely heavily on them for resources and diversity (Weiss 2018; Dörnhöfer and Oppelt 2016). Future work is needed to use land and water trend comparisons to identify lakes undergoing water loss or related environmental challenges.

Together in a Bayesian linear model, lake type and changing surface area status predict net change in temperature. Future work could also be done to identify the relationship between lake type and lake water loss. Preliminary analysis in figure 9 suggests that natural lakes are more susceptible to water loss than regulated human-made natural lakes, which could be supported by the differences between lake types highlighted in Hayes et al. (2017).

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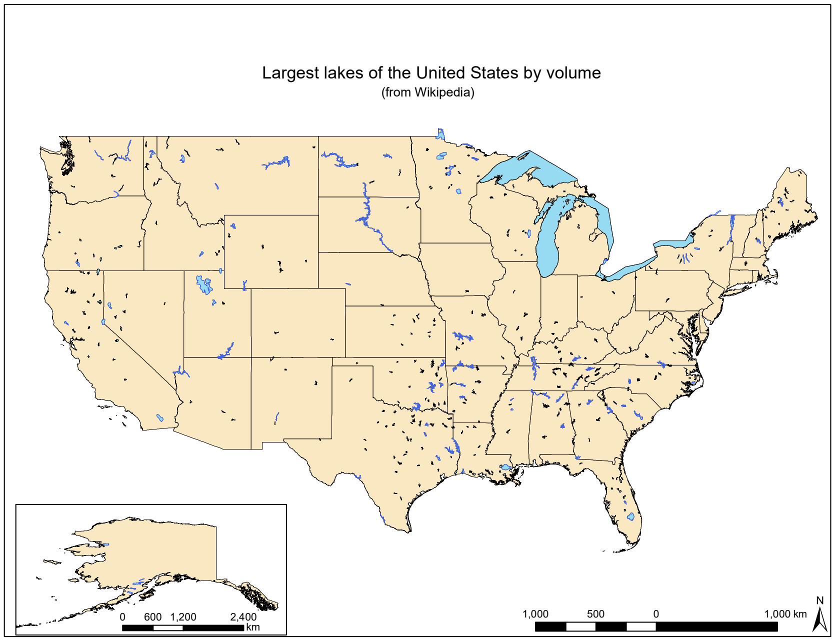

Figure 1: Pinpointed locations of 95 largest lakes (excluding the Great Lakes) for analysis in the United States with surface areas greater than 100 km^2.

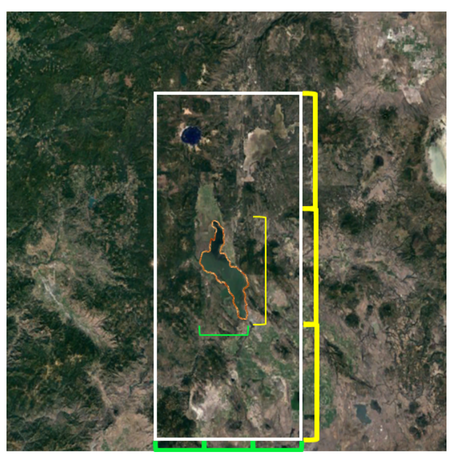

Figure 2: To calculate surrounding land temperatures for each lake, we used the land area in the white box, excluding the lake area boarded in orange. The land area is 9 times the lake area, since three times the length and width of the lake was used to create the white box area. Yellow indicates the length of the lake, and green indicates the width of the lake.

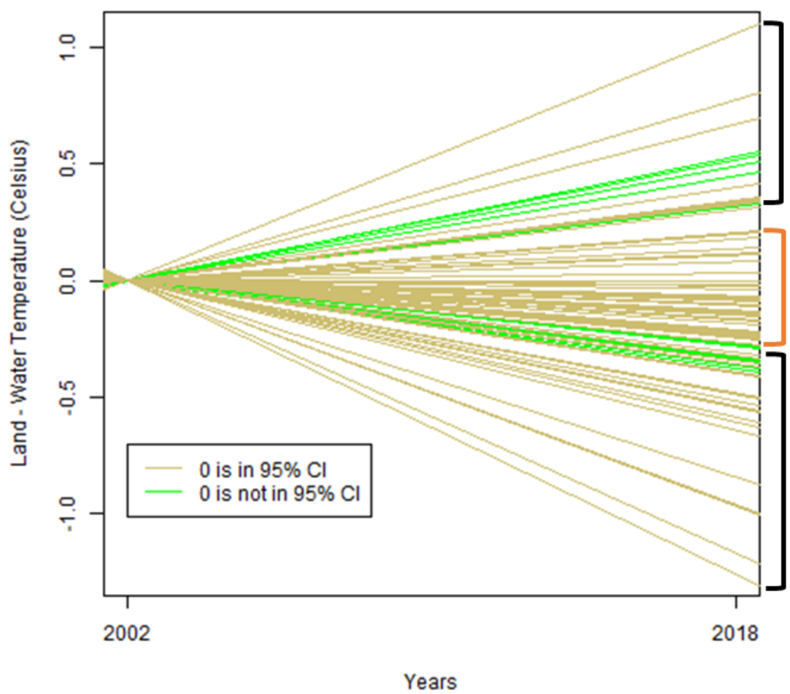

Figure 3: Each line indicates the net change in temperature between surrounding land and lake surface water temperature between 2002 and 2018. These values were predicted using the slope of the Bayesian linear model for each lake ($n = 95$). Using 95% credible intervals, the green lines indicates lakes whose CI did not contain 0, meaning we are 95% certain these lakes had different land and water trends. The tan lines indicate lakes whose CI contained 0. If the estimate was close to 0, then we are more certain the land and water had similar trends (orange bracket), whereas if the estimate was large, we are less certain on that estimate (black brackets).

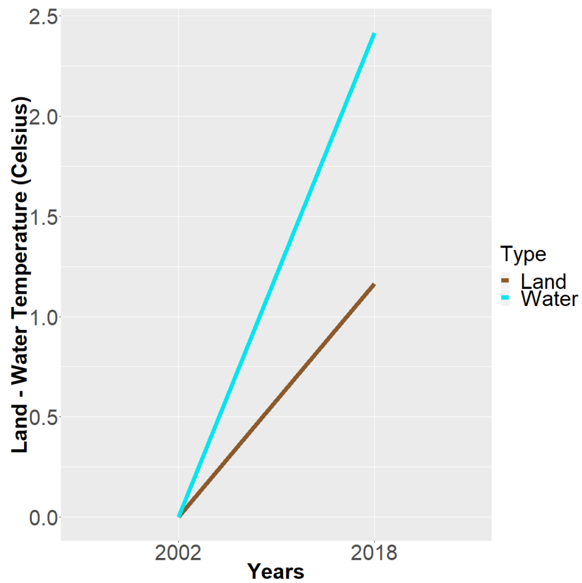

Figure 4: Land and water trends for two lakes that whose water temperature had a higher rate than the land temperature, meaning the estimated net change in temperature given in figure 3 was negative. Left: In figure 3, Lake Mead is the bottom tan line. Right: In figure 3, Lake Hartwell is the bottom green line.

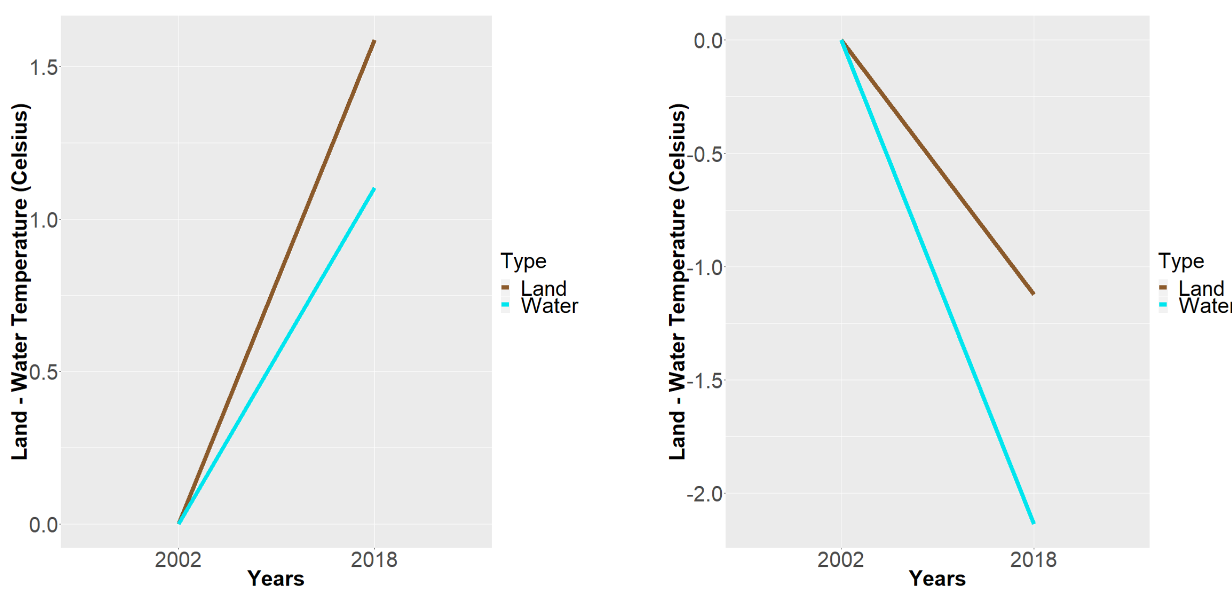

Figure 5: Land and water trends for two lakes that whose land temperature had a higher rate than the water temperature, meaning the estimated net change in temperature given in figure 3 was positive. Left: In figure 3, Lake Iliamna is the top green line. Right: In figure 3, Lake McConaughy is the top tan line.

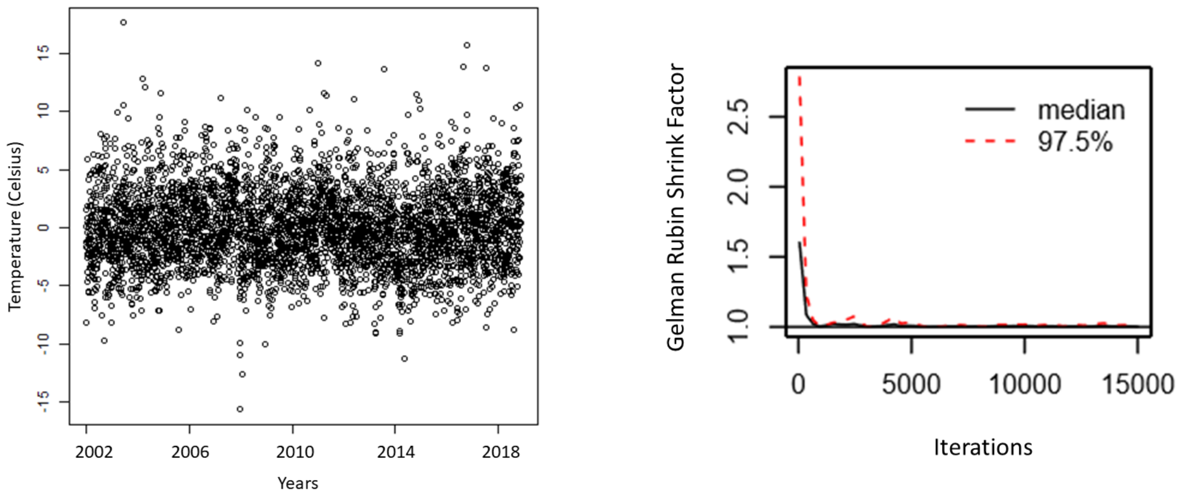

Figure 6: Klamath Lake trend difference model validations. Uncorrelated residuals for the final model (left). Gelman Rubin convergence plot for the intercept, converged around 5000 iterations (right). All other parameters in the model converged similarly. All lakes for each of the 95 trend difference models reflected these residual and Gelman Rubin convergence plots.

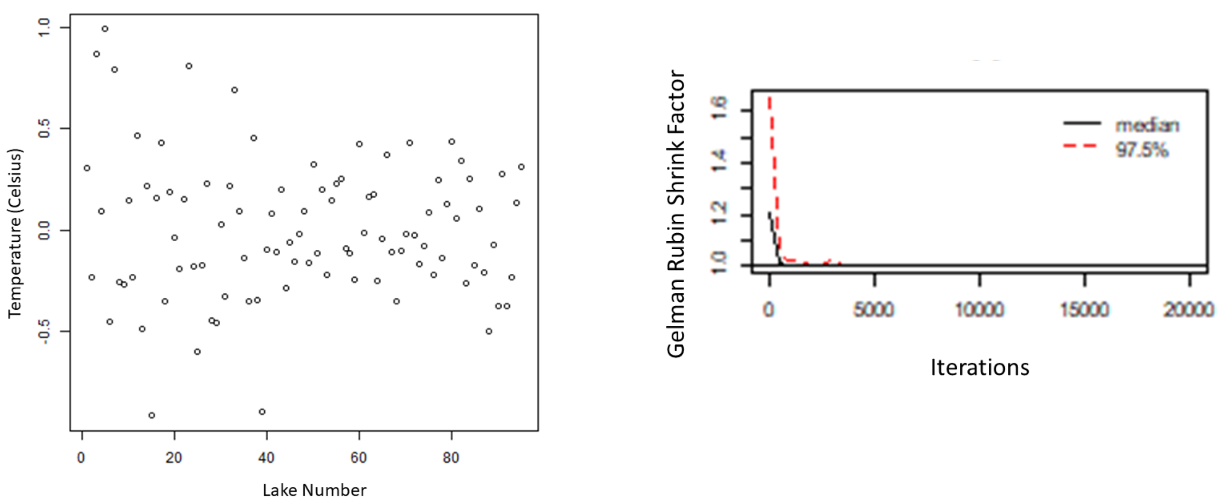

Figure 7: Final model validations. Uncorrelated residuals for the final model (left). Gelman Rubin convergence plot for the intercept of the final model, converged around 5000 iterations (right). All other parameters in the final model converged similarly.

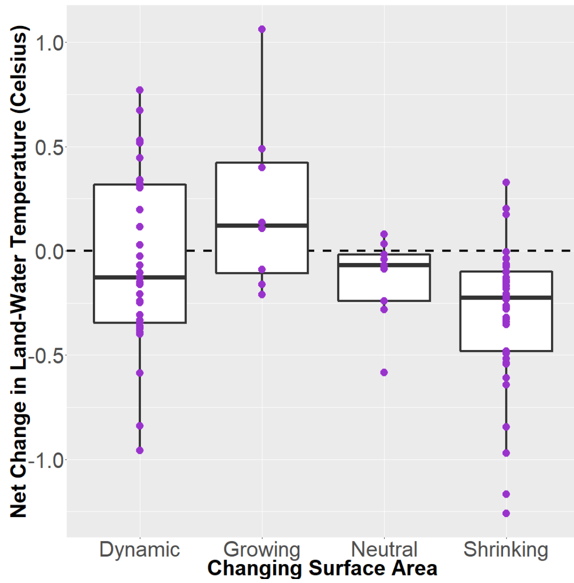

Figure 8: Changing surface area status isolated with net change in temperature difference between land and water. Each purple dot represents one lake ($n = 95$). The shrinking lakes interquartile range is below 0, indicating that shirnking lakes have water temperature rates that are higher than land temperature rates. Growing lakes median is above 0, indicating that growing lakes have land temperature rates that are higher than water temperature rates. Neutral lakes interquartile range is close to 0, indicating that neutral lakes have similar land and water rates. Dynamic lakes interquartile range is spread over positive and negative ranges, indicating the nature of this variable category.

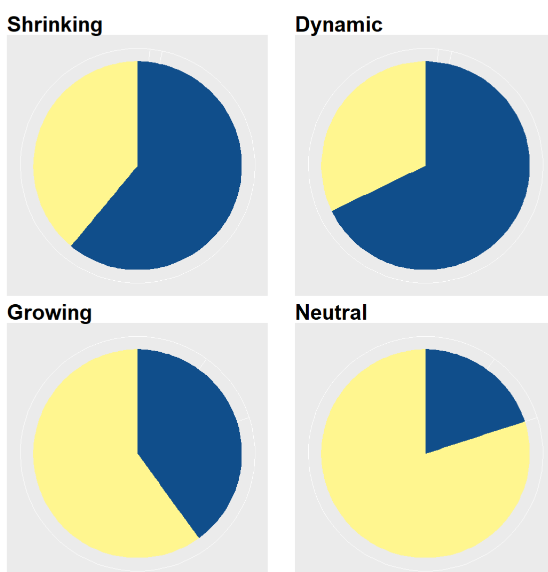

Figure 9: Preliminary analysis on lake type and changing surface area status. The blue indicates the proportion of natural lakes, and the yellow indicates the proportion of human-made lakes in each changing surface area status category.