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Influences of local weather, large-scale climatic drivers, and the *ca*. 11 year solar cycle on lake ice breakup dates; 1905–2004

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Abstract We investigate the temporal patterns in inter-annual variability in ice break-up dates for Lakes Mendota and Monona, Wisconsin, between 1905 and 2004. We analyze the contributions of long-term trends attributed to climate change, local weather, indices of sunspots, and large-scale climatic drivers, such as the North Atlantic Oscillation (NAO) and El Niño Southern Ocean Index (ENSO) on time series of lake-ice breakup. The relative importance of the aforementioned explanatory variables was assessed using linear regression and variation partitioning models accounting for cyclic temporal dynamics as represented by Moran Eigenvector Maps (MEM). Model results explain an average of 58 % of the variation in ice breakup dates. A combination of the long-term linear trends, rain and snowfall in the month prior to breakup, air temperature in the winter prior to breakup, cyclic dynamics associated with sunspot numbers, ENSO, and for Lake Mendota, NAO, all significantly influence the timing of ice breakup. Significant cycle lengths were 3.5, 9, 11, and 50 years. Despite their proximity, Lakes Mendota and Monona exhibit differences in how and which explanatory variables were incorporated into the models. Our results indicate that lake ice dynamics are complex in both lakes and multiple interacting processes explain the residuals around the linear warming trends that characterize lake ice records.

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1 Introduction

Lake ice records are sensitive indicators of climate change and variability. Lake ice records can serve as surrogates to estimate air temperatures (Assel and Robertson 1995; Vavrus et al. 1996; Mudelsee 2012) and as sentinels of climate change (Adrian et al. 2009). Ice seasonality of lakes has changed over time and across the Northern Hemisphere, with later freezing, earlier breakup, and shorter ice cover duration over the past 100 to 200 years (Kuusisto 1987; Robertson et al. 1992; Magnuson et al. 2000; Weyhenmeyer et al. 2011; Benson et al. 2012). While the slopes of the regressions for lakes around the Northern Hemisphere are usually significant at $p \leq 0.01$ (Magnuson et al. 2000), the proportion of variation actually explained in the trends in ice dates has been low. For example, ice breakup for Lake Mendota, Wisconsin, has occurred 7.7 days earlier per century ($p < 0.0001$) over the last 150 years, but a linear relation of breakup date against year only explains 9 % of that variation (Magnuson 2010). The remaining 91 % remains unexplained.

Thus, the relationship between ice breakup dates over time provides a noisy and complex record of linear trends and variability at interannual and interdecadal scales. Some of the unexplained variation in ice dates, i. e., residuals around the linear trend, is associated with large-scale climate drivers such as the El Niño Southern Oscillation (ENSO), Pacific Decadal Oscillation (PDO), and North Atlantic Oscillation (NAO) (Livingstone 2000; Robertson et al. 2000; Magnuson et al. 2004; Ghanbari et al. 2009; Bai et al. 2012; Benson et al. 2012; Mudelsee 2012). However, a large portion of the variation remains unexplained even after the indices of individual large-scale drivers are related to ice breakup dates. Local weather prior to ice breakup also contributes to the noisy time series. Air temperature, snowfall and snow depth exhibit coherent patterns with ice dynamics (Palecki and Barry 1986; Vavrus et al. 1996; Ghanbari et al. 2009; Benson et al. 2012). Variations in winds, cloud cover, and solar radiation in the days prior to ice breakup can affect the timing of ice breakup dates and explain additional variation in ice breakup dates over time (Palecki and Barry 1986; Vavrus et al. 1996; Lepparanta and Wang 2008; Jakkila et al. 2009).

The overall objective of our study is to estimate the proportions of variation associated with linear trends, large-scale climatic drivers, and local weather using the time series of ice breakup dates for Lakes Mendota and Monona, Wisconsin, between 1905 and 2004.

2 Methods

2.1 Data acquisition

Ice breakup time series for Lakes Mendota and Monona, Dane County, Wisconsin spanning 100 years for the winters of 1904–5 to 2003–4 were studied (Appendix 1). As defined by the Wisconsin State Climatologist, for Lake Mendota, the ice breakup date is when the lake is ice-free from Picnic Point to Maple Bluff and total ice cover is less than 50 %. For Lake Monona, the ice breakup date is the last date the ice breaks before the lake becomes open. On average since 1855, Lakes Mendota and Monona are covered with ice for 105 days of the year (ranging between 47–160 days per year). The lakes are adjacent to each other, separated by a narrow isthmus of approximately 1.2 km.; the outlet of Mendota flows into Monona. They differ in physical characteristics, for examples, with areas (ha) of 3,938 for Mendota and 1,324 for Monona, and mean depths (m) of 12.8 for Mendota and 8.2 for Monona (Magnuson et al. 2006).

Ice breakups dates were acquired from the North Temperate Lakes Long Term Ecological Research database. These lakes and years were used because the ice record is complete and weather and indices for large-scale drivers are available for the same winters. Weather data were "*daily*" weather for the 32 days prior to the breakup dates and for the "*winter*" averaged for December, January and February. Weather data in the form of daily air temperature, precipitation, and snow depth were obtained for Madison, Wisconsin, from the State of Wisconsin Climatology Office and accessed from the North Temperate Lakes Long Term Ecological Research database. Time series for the sunspot numbers (total number of sunspots per year) and the large-scale climatic drivers were acquired from various databases (Appendix 2) and included the Atlantic Multidecadal Oscillation (AMO), El Niño Southern Oscillation Index (ENSO), North Atlantic Oscillation (NAO), North Pacific Index (NP), and Pacific Decadal Oscillation (PDO). We used the mean annual values and the winter mean (December-March) for all indices.

2.2 Data analyses

A statistical framework was devised to meet our objectives (Appendix 1). First, the simple linear trend in the ice records over time was estimated and the residuals were used for further analyses. Second, an autocorrelation function analyses determined whether temporal dependency was a dominant feature of the time series. Subsequently, given the absence of temporal autocorrelation, a multiple regression model related ice breakup dates to significant environmental drivers (local daily weather (*daily*), local winter weather (*winter*), indices of sunspots and large-scale drivers (*indices*)). In parallel to the development of the multiple regression model, we performed a time-frequency analysis using Moran Eigenvector Maps (MEM) to identify the important temporal cycles (*cycles*) in the ice record. Lastly, we performed a variation partitioning analyses to identify the relative contribution of environmental drivers on ice records. Explanatory variables in this model were the significant environmental variables identified in the multiple regression model and the important temporal cycles identified by the MEM analyses above (Appendix 3).

i) Trends and autocorrelation

   Linear regression was used to analyze the relationship between ice breakup dates and year. Subsequent analyses were performed on the residuals of the detrended data. An autocorrelation function (ACF) and a partial autocorrelation function (PACF) were used to assess the serial temporal correlation in the ice-breakup time series at different lags in the series.

ii) Multiple regression model

   A multiple regression model related ice breakup dates and the hypothesized explanatory variables. Because the number of predictor variables was large, a forward selection procedure was employed to select significant variables. Only predictor variables with $p < 0.05$ were retained in the model. Selection of a final multiple regression model relating ice breakup dates to *daily* weather, *winter* weather, *indices* of sunspots and large-scale drivers was based on the Akaike Information Criterion (AIC). The model with the lowest AIC value was chosen as the most parsimonious model.

iii) Cyclic temporal dynamics

   Moran Eigenvector Maps (MEM) identified oscillatory dynamics in ice breakup time series using the residuals generated from the linear model (see (i) above). The MEM approach generates a series of sine waves with decreasing periods that are orthogonal to one another and can be used as a set of independent variables in a subsequent analysis, such as linear regression, redundancy analysis or a variation partitioning framework. The MEM approach in this study is a novel method to elucidate cycles in the time-series data that occur with different periods. The first MEM-variables represented the broad temporal cycles, and subsequent MEM variables represent cycles with decreasing periods (see Appendix 4 (this study); Borcard and Legendre 2002 for details).

iv) Variation partitioning model

Significant environmental variables from (ii) and significant temporal cycles from (iii) were used as predictor variables in the variation partitioning model (Appendix 3). We identified the percentage of variation explained on ice breakup dates by local Madison weather (*daily* in the month prior to breakup, or the average of the three *winter* months), the *indices* of sunspot numbers and large-scale climate drivers, and *cyclic* temporal dynamics as represented by MEM variables. The variation explained in the ice breakup record was quantified by partitioning the variation explained by each component using a series of redundancy and partial redundancy analyses (see Borcard et al. 1992 for further details). For each explanatory variable and for each interaction between and among explanatory variables, we quantified the unique and shared variation explained by each component on ice breakup dates over time. We summarized the variation explained by each component by calculating the adjusted R^2. All data manipulation and statistical analyses were performed in the R-language environment (R Development Core Team 2012).

3 Results

3.1 Trends and autocorrelation

Trends of ice breakup dates for Lakes Mendota and Monona both have negative slopes indicating earlier ice breakup dates over the 100 years from 1904–5 to 2003–4 (Fig. 1). Lake Mendota broke up 6.7 days earlier per century ($p<0.05$) and Lake Monona 12 days earlier ($p<0.0005$). The relationships are statistically significant but explains a relatively small portion of the variation in the two times series especially for Lake Mendota. The linear trend explains 2.5 % (Lake Mendota) and 10.8 % (Lake Monona) of the variation in the time series. Over the corresponding time series (1905–2004), winter air temperatures in Madison, Wisconsin have warmed approximately 2.5 °C over the century (Fig. 1c). The linear trend in winter air temperatures explains 7.6 % of the variation in the time-series. Thus, the ice breakup time series are consistent with a warming climate.

For both Lakes Mendota and Monona, the autocorrelation function (ACF) plot exhibits no significant correlations ($p<0.05$) between any data point to previous data points in the time series (Appendix 5). Similarly, the partial autocorrelation function (PACF) plots reveal no significant correlations ($p<0.05$) that are unexplained by autocorrelation at shorter lags in the time series (Appendix 6). The absence of temporal autocorrelation suggests that the memory of an ice break-up date from a previous year does not influence ice break-up date in the present year. Thus, a multiple regression model without an autoregressive moving average component is appropriate for analyses of these time-series.

3.2 Multiple regression model

The most parsimonious multiple regression model that best predicts ice breakup dates for Lake Mendota is:

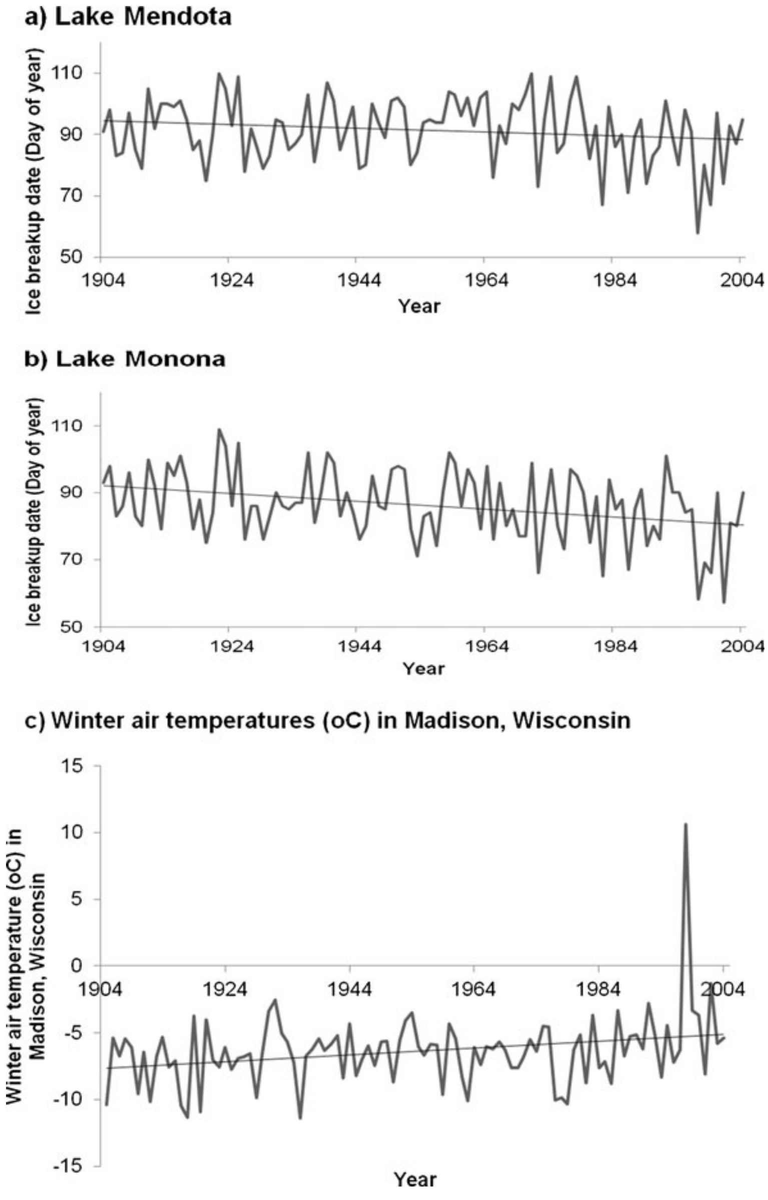

Fig. 1 Ice breakup dates over 1905–2004 in (**a**) Lake Mendota and (**b**) Lake Monona. **c** Winter air temperatures (°C) in Madison, Wisconsin over the corresponding 100 year time period. The *line* represents the linear trend through the time series

$$\begin{aligned}\text{Ice breakup date} = {} & 76.4 - 2.0(\text{NAO index}) - 1.7(\text{winter air temperature}) + \text{daily weatheras} \\ & + 0.4\left(\text{rain}_{\text{day6}}\right) + 0.6\left(\text{rain}_{\text{day17}}\right) + 0.7\left(\text{rain}_{\text{day26}}\right) + 0.6\left(\text{rain}_{\text{day31}}\right) \\ & + 0.7\left(\text{snowfall}_{\text{day19}}\right) + 0.7\left(\text{snowfall}_{\text{day20}}\right)\end{aligned}$$

where

NAO North Atlantic Oscillation Index
day n nth date prior to ice breakup date

The Lake Mendota ice breakup model is significant at $p<0.00001$ and all predictor variables are significant at $p<0.05$. The adjusted R^2 of the model is 43 % and this model is the most parsimonious based on the lowest AIC value. Of the 43 % of explained variation, *daily* precipitation explains 26 % and *daily* snowfall explains 17 %, *winter* average weather temperatures explains 40 %, and the NAO *index* explains 18 % of the variation in ice breakup dates. The amount of variation explained by precipitation in the month prior to breakup was similar (43 %) to the amount of variation explained by winter temperatures averaged for December, January and February (40 %).

The most parsimonious multiple regression model that best predicts ice breakup dates for Lake Monona is:

$$\text{Ice breakup date} = 73.8 - 1.7(\text{winter air temperature}) + \text{daily weather as} - 0.5\left(\text{rain}_{\text{day7}}\right)$$
$$+ 0.5\left(\text{rain}_{\text{day14}}\right) + 1.1\left(\text{rain}_{\text{day19}}\right) + 0.8\left(\text{rain}_{\text{day28}}\right)$$

The Monona ice breakup model is significant at $p<0.00001$ and all predictor variables are significant at $p<0.05$. The adjusted R^2 of the model is 36 % and this model is the most parsimonious based on the lowest AIC value. Of the 36 % of explained variation, *daily* precipitation explains 61 % and average *winter* temperatures explains 39 % of the variation in ice breakup dates. No variation is explained by the *indices* representing large-scale climatic drivers or the sunspot index.

3.3 Cyclic temporal dynamics

Significant cyclic dynamics are apparent in the breakup time series (residuals from the linear regression) that correspond with known oscillatory dynamics of sunspot numbers and large-scale climate drivers. The MEM variables corresponding to oscillatory cycles of 3.5, 9, 12, and 50 years are statistically significant ($p<0.05$) in explaining variation in ice breakup dates. Together, these cycles explained a total of approximately 27 % additional variation for Lake Mendota and 23 % for Lake Monona. The 3.5-yearcycle explain 10.6 % (Mendota) and 7.1 % (Monona) of the variation in ice breakup dates. The 9-yearcycle explains 5.6 % (Mendota) and 8.8 % (Monona) of the variation. The 12-yearcycle explains 3.4 % (Mendota) and 3.9 % (Monona) of the variation. Finally, the 50-yearcycle explains 3.7 % (Mendota) and 0.0 % (Monona) of the variation in ice breakup dates.

3.4 Variation partitioning model

The concept of unique and shared contributions is illustrated with examples for Lake Mendota and Lake Monona in Appendix 7. The percentage of variation in the time series from various drivers are presented in Table 1. The variation accounted for by the linear trends average 6.7 % across the two lakes. Subsequently, the unique and shared variation from the residuals of those linear trends are presented from our final MEM model and average 52 % across both lakes.

In addition to the variation explained by the linear *trend*, the unique plus shared contributions of the aforementioned drivers explain an additional 51 % (Mendota) and

Table 1 Unique and shared contribution of each group of explanatory variables (local daily weather (*daily*), local winter weather (*winter*), temporal oscillatory cycles (*cycles*), indices of sunspots and large-scale climatic drivers (*indices*)) on ice breakup patterns of Lakes Mendota and Monona

	Adjusted R2		
Variable	Mendota	Monona	Mean
1) Linear trend	2.5	10.8	6.7
2) Unique contributions			
Daily	13.7	17.8	15.8
Cycles	5.8	18.3	12.0
Winter	8.1	4.1	6.1
Indices	1.3	0	0.7
Total unique contributions	*28.9*	*40.2*	*34.6*
3) Two Variable Shared Contributions			
Daily + Winter	1.5	9.7	5.6
Daily + Cycles	7.9	0	4.0
Cycles + Indices	3.5	0	1.8
Winter + Cycles	1.6	1.8	1.7
Winter + Indices	0.2	0	0.1
Daily + Indices	0	0	0.0
Total Two Variable Shared Contributions	*14.7*	*11.5*	*13.2*
4) Three & Four Variables Shared Contributions			
Daily + Winter + Cycles	3.4	0	1.7
Daily + Indices + Cycles	1.7	0	0.9
Daily + Winter + Indices	0	1.2	0.6
Winter + Indices + Cycles	0.7	0	0.4
Daily + Winter + Indices + Cycles	1.3	0	0.7
Total Three & Four Variable Shared Contributions	*7.1*	*1.2*	*4.3*
Total of all Shared contributions	*21.8*	*12.7*	*17.5*
5) Total explained variation (Unique, Shared and Trend)	***53.2***	***63.7***	***58.8***

Adjusted percent variation are summarised. Linear trend is derived from linear regression models of ice breakup dates with time. Total contributions for each group of variables are summarised for unique, shared, and unique + shared contributions.

53 % (Monona) of the variation (Table 1, Fig. 2). The unique contributions are greater than the shared contributions. The unique contributions of *cycles*, *indices*, *daily*, and *winter* totalled 29 % (Mendota) and 44 % (Monona) while the shared contributions of these same explanatory variables were 22 % (Mendota) and 13 % (Monona). The combination of *daily* local weather in the month prior to breakup, precipitation and snowfall, and *cycle* lengths of 3.5, 9, 12, and 50 years, explain the most variation in ice breakup dates. Average w*inter* local temperatures explain over 10 % of the variation in ice breakup dates. *Indices* of large-scale drivers explain little (Mendota) or no (Monona) variation (Fig. 2).

Lake Monona has a higher proportion of variation explained by unique contributions of environmental variables whereas Lake Mendota has a higher proportion of variation explained by shared contributions (Table 1; Fig. 2). The variation ascribed to unique contributions of individual variables appears to be compensated by the shared contributions.

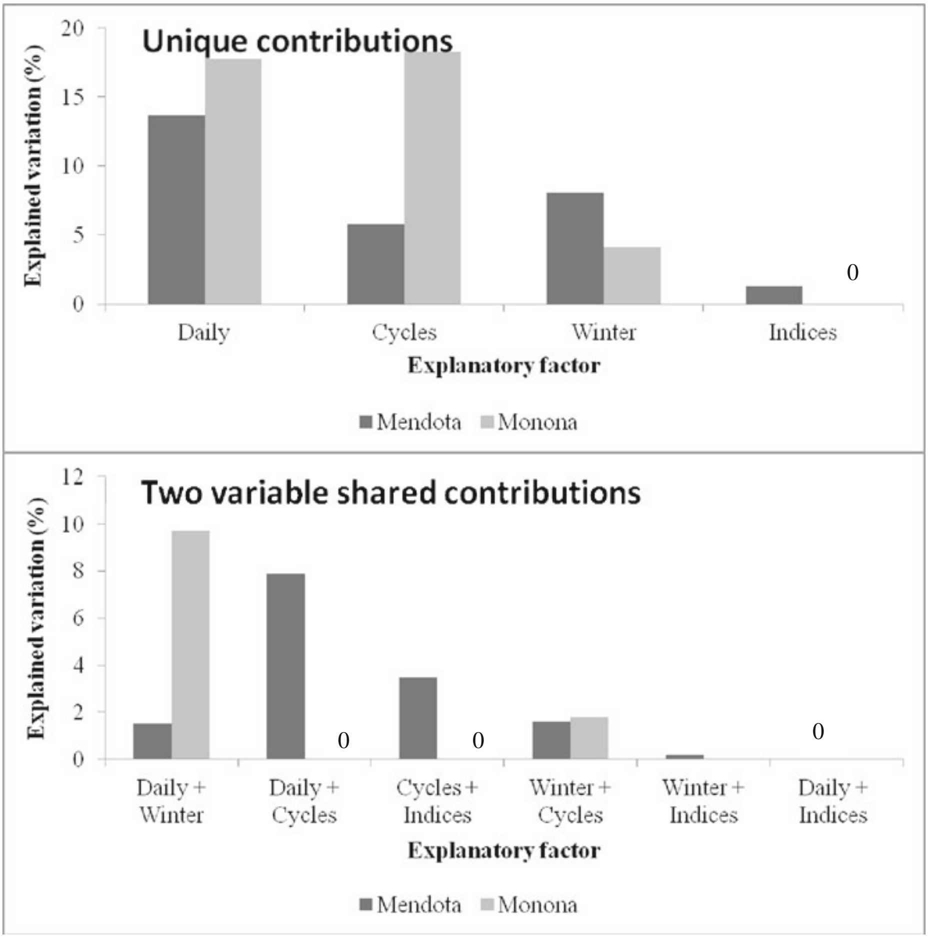

Fig. 2 Total unique (**a**) and two variable shared contributions (**b**) of each group of variables (local daily weather (*Daily*), local winter weather (*Winter*), temporal oscillatory cycles (*Cycles*), indices of sunspots and large-scale climatic drivers (*Indices*) on ice breakup patterns of Lakes Mendota and Monona. Adjusted percent variation explained is summarised

Nonetheless the overall variation explained by the environmental variables was similar in both lakes. These results indicate the complexity of the climate and weather system that contributes to the variation in ice records.

4 Discussion

Our goal was to provide some insight about the relative importance of the various influences on ice breakup dates (long-term linear trends, indices for solar sunspots and large-scale climatic drivers, and local weather) acting in concert with each other rather than acting individually. We accounted for 53 % (Lake Mendota) and 64 % (Lake Monona) of the variation in ice breakup. Significant components of the variation were precipitation and snowfall in the month before ice breakup (*daily*), average winter air temperatures (*winter*), NAO Index (*indices*), cycles lengths of 3.5, 9, 12, and 50 years (*cycles*), and a long-term warming trend associated with climate change. On average in both lakes, *daily* weather and oscillatory dynamics (*cycles*) explained most of the variation in ice breakup dates. Less variation was explained by solar sunspots, large-scale climatic drivers, and local winter weather.

4.1 Local conditions

Local *daily* weather represents the weather immediately prior to ice breakup and the processes that would delay or accelerate the ice breakup in that year. The most significant variables were rain and snowfall based on our multiple regression model. Surprisingly, precipitation events prior to ice breakup delayed breakup, rather than causing an earlier breakup. Rainfall could have delayed ice breakup by decreasing the amount of solar radiation reaching the lake surfaces associated with increased cloud cover (Palecki and Barry 1986; Vavrus et al. 1996; Adrian et al. 2009; Jakkila et al. 2009). Increased snowfall also suggests cloudier conditions but thicker snow on the ice would further reduce levels of solar radiation reaching the lake surface and delay ice breakup (Palecki and Barry 1986; Vavrus et al. 1996; Adrian et al. 2009; Jakkila et al. 2009). Conversely, less snow cover on the ice would have increased transmission of solar radiation and light penetration into the lake, thereby accelerating ice breakup (Lepparanta and Wang 2008; Erm et al. 2010). Other alternative mechanisms that could accelerate ice breakup include warmer air temperatures (Vavrus et al. 1996), stronger winds (Lepparanta and Wang 2008), and increased water present on the ice (Lepparanta and Wang 2008). However, these alternative mechanisms were not indicated by our analyses as ice breakup dates were delayed rather than accelerated.

Air temperatures averaged over the winter season influence ice breakup dates in an expected direction. Colder winters exhibited a later ice breakup date, whereas ice melted earlier following a warmer winter. In Northern Hemisphere lakes, air temperature may be the most important meteorological forcing factor explaining ice conditions (Palecki and Barry 1986; Assel and Robertson 1995; Vavrus et al. 1996; Livingstone 2000; Korhonen 2006; Benson et al. 2012), such that years with elevated air temperatures have correspondingly shorter duration of ice coverage (Benson et al. 2012). Over the past century in Madison, Wisconsin, warming winter temperatures have been associated with earlier ice breakup and decreases in ice-cover duration (Ghanbari et al. 2009). Cooler temperatures even in the month before ice breakup, can delay breakup. Palecki and Barry (1986) observed a strong correlation between ice breakup date and air temperatures 5 to 10 days prior to ice breakup in southern Finnish lakes.

4.2 Sunspot numbers and large-scale climate drivers

We identified the NAO Index and cycles with lengths of 3.5, 9, 12, and 50 years as significant large-scale drivers. The cycle lengths could be successively attributed to the El Niño Southern Oscillation (ENSO), sunspot numbers, and the North Atlantic Oscillation (NAO). In comparison, spectral analysis of Lake Näsijärvi, Finland observed significant cycle lengths of 2, 3.5, and 42 years on ice breakup dates (Mudelsee 2012).

To our knowledge, these analyses are the first to quantify a relation between cycles of solar sunspot activity and ice breakup dates of lakes. The sunspot cycle refers to solar magnetic activity and is quantified as the number of spots present on the sun. In both Lakes Mendota and Monona, we observed significant cycle lengths of 9 and 12 years which are close to the length typically ascribed to sunspot numbers. The average length of the sunspot cycle has been identified as approximately an 11 yearcycle (Chrstensen and Lassen 1991;

Lee et al. 1995), although there is variation in cycle length particularly in the latter half of the 20th century as greenhouse gas emissions have increased (Chrstensen and Lassen 1991). Solar activity has been linked to indicators of global climate (Eddy 1976), sea surface temperatures (Reid 1987) and levels of sea ice in Iceland (Chrstensen and Lassen 1991).

The influence of the North Atlantic Oscillation was only apparent in Lake Mendota through significant relationships with the NAO Index and cycle length of approximately 50 years. The most recent full cycle length for NAO is about 50 years which is also similar to the length of the Atlantic Multidecadal Oscillation (AMO) and the Pacific Decadal Oscillation (PDO) (Trenberth et al. 2007). No variation was explained by NAO for Lake Monona. High winter NAO indices are indicative of strong westerly winds and warmer temperatures; the reverse is true for low winter NAO indices (Hurrell 1995; Blenckner et al. 2007; Bai et al. 2012). In previous studies, the winter NAO index has been correlated strongly with ice breakup dates in Lake Mendota and lakes across the Northern Hemisphere (Livingstone 2000; George et al. 2004; Magnuson et al. 2004; Ghanbari et al. 2009; Karetnikov and Naumenko 2011) and appears to act at very broad temporal scales, such that coherent patterns between ice conditions and the NAO index appear to occur inter-decadally (Ghanbari et al. 2009). It has been suggested that NAO may influence ice breakup dates through its effects on winter air temperature (Blenckner et al. 2007), snowfall (Ghanbari et al. 2009), and alteration in strengths of southerly and westerly winds (Bai et al. 2012). We should also note that the 100 year ice record only accounts for 2 cycles of the NAO and consequently may underestimate its influence in both lakes.

In both lakes, we observed a cycle length of 3.5 years that may capture some of the variation associated with El Niño Southern Oscillation, although we did not find a direct relationship with the ENSO Index and ice breakup date. This cycle length is similar to the cycle observed in a southern Finland lake (Mudelsee 2012). In North America, ENSO has been observed to correspond to winter atmospheric circulation, winter air temperatures, ice cover, and heat balances of lakes (Livingstone 2000) and appears to have a cycle of 3–7 years (Trenberth et al. 2007). In previous analyses of ice dynamics, ENSO appears to be related to ice breakup dates such that El Niňo events corresponded to later ice breakup (Anderson et al. 1996; Livingstone 2000; Robertson et al. 2000; Bonsal et al. 2006) and lower ice cover (Bai et al. 2012). However, this relationship appears to be weaker or even switch prior to 1940 (Livingstone 2000; Robertson et al. 2000). Prior to 1940, cooler air temperatures were evident in late winter of El Niňo years, whereas following 1940 warmer air temperatures were evident in late winter of El Niňo years (Robertson et al. 2000). However, La Nina events do not have significant impacts on Great Lakes regional winter climate (Bai et al. 2012). The ENSO Index appears to act an inter-annual scale, but may act at an inter-decadal scale through its interaction with the NAO. The ENSO and NAO have been shown to interact with one another in the Great Lakes whereby the Great Lakes tend to have less ice cover during El Niño and positive NAO events and more ice cover in La Niňa and negative NAO events (Bai et al. 2012). However if the lakes were larger, there may have been an even stronger signal of ice breakup dates to the indices of the large-scale climatic drivers and the solar sunspot cycle. Smaller-sized lakes may have a boundary constraint that may limit ice growth and thereby their sensitivity to large-scale climatic drivers or the solar sunspot cycle (Wang et al. 1994).

4.3 Long-term warming trends

In our study, the linear trends were statistically significant but explained small amounts of variation. Lake Mendota is breaking up 6.7 days earlier per century, whereas Lake Monona is breaking up 12 days earlier per century. The average rate of change in ice breakup for 71 lakes around the Northern Hemisphere is 5.2 days per century (Benson et al. 2012). Despite their close proximity to one another, Lakes Mendota and Monona have different rates of change in ice breakup both here and in Magnuson et al. (2000). The more rapid warming of Lake Monona over the past 100 years could be attributed to both changes in climate and the presence of an electric power generating plant that has been successively introducing more waste heat into the lake with increased power production over the years. No such powerplant exists on Lake Mendota. However since 1976, Lake Mendota has been melting at a rate of 5.3 days earlier per decade which is indicative of a warming trend that could be attributed to climate change. Lake Monona has been exhibiting similar rates of melting since 1961. This pattern is consistent across 75 lakes in the Northern Hemisphere (Benson et al. 2012). Within the past 150 years, lakes are experiencing even more rapid melting rates in the past 30 years relative to earlier time periods (Benson et al. 2012). For example, on average lakes were melting 1.9 days earlier per decade in the past 30 years compared to 0.5 days earlier per decade in the past 100 years.

4.4 Comparison of Lakes Mendota and Monona

The variation partitioning model including the long-term trends explained more of the variation for Lake Monona (64 %) than for Lake Mendota (53 %) (Table 1). The 11 % difference between the two lakes is of a similar magnitude as the difference in the variation (8 %) explained only by the linear trends. The presence of an electric power generation plant on Lake Monona may be a significant contributor to the difference in explained variation between the two lakes. The electric power generation plant was installed in 1923. Since 1923-present, electrical production has grown by a factor of 200 (www.mge.com). The powerplant may play an additional role in explaining the absence of a significant NAO signal for Lake Monona whereas a significant NAO signal exists for Lake Mendota. It is tempting to hypothesize that the amount of heat produced by the powerplant differs between phases in the NAO owing to differences in demand for power generation in the colder phases. We should also note that the 100 year ice record only accounts for 2 cycles of the NAO and consequently may underestimate its influence in both lakes. It may also be possible that if there were a heat island effect of Madison, Wisconsin, it would be more influential on Lake Monona than Lake Mendota.

Closer examination of the unique and shared contributions between the two lakes is much more complex. For example, for the total unique contributions, a higher percent of variation is explained for Lake Monona (40 %) than for Lake Mendota (29 %). Conversely, shared contributions explain a higher percent of variation for Lake Mendota (22 %) than for Lake Monona (13 %). For example, the percent variation explained by unique contributions of *cycles* suggests that Lake Monona has a higher percentage of variation in ice breakup dates explained by *cycles* (18 %) than for Lake Mendota (6 %). However, shared contributions of *cycles*, explain a higher percent of variation for Lake Mendota (20 %) than for Lake Monona (3 %). When unique and shared variations are considered together, the variation explained by cycles is similar for both lakes.

What explains the differences in the interplay between unique and shared contributions in the two lakes? One explanation may result from the complexity of the analyses that may not account for the same explanatory variables in the same manner. Alternatively, Lake Mendota may be characterized by more complex interrelationships among the explanatory variables than Lake Monona because the lakes differ in physical characteristics; for example, Lake Mendota has a larger surface area, volume, and fetch, deeper depth, and slower turnover times than Lake Monona (Magnuson et al. 2006). Additional factors may explain the differences between the lakes, such as differences in the energy fluxes driving lake ice breakup in the two lakes including: lake size, shape, and the amount of snow cover on top of the lake (Vavrus et al. 1996). For example, lake size and shape may alter the amount of solar radiation absorbed on the land warming smaller lakes faster than larger lakes owing to the larger relative shoreline fraction (Scott 1964; Vavrus et al. 1996). Also, the presence of the electric powerplant on Lake Monona may simplify the interaction with other explanatory variables by providing more thermal input into the lake over time and a stronger linear trend from which to explain the residuals in ice breakup dates.

4.5 The warming trend and residual variability

We had statistically significant linear trends in ice breakup in both Lakes Mendota and Monona. This is consistent with many studies that consistently reveal that lake ice breakup is becoming earlier around the Northern Hemisphere (e.g., Kuusisto 1987; Robertson et al. 1992; Magnuson et al. 2000; Weyhenmeyer et al. 2011; Benson et al. 2012). The average breakup date from an anomaly time series from 17 lakes from1855–6 though 2004–5 shares 37 % of its variability with global spring air temperatures over land (Benson et al. 2012). The relations between lake ice and temperature are strong enough that lake ice can be used as a surrogate to estimate past air temperatures (Assel and Robertson 1995; Mudelsee 2012). In a few cases local anthropogenic factors add to the steepness of the slopes; two examples are Lake Monona with heat additions from an electric power generation plant (this paper) and Toronto Harbor with major changes to the bay and the urbanization of Toronto (Magnuson et al. 2000). These lakes are exceptions, as most other lake ice records analyzed are found imbedded in forested and other more natural landscapes.

Clearly our results indicate that lake ice dynamics are complex and have multiple interacting explanatory processes at work. This complexity produces the noisy time series of ice breakup dates for lakes Mendota and Monona and for other lakes around the Northern Hemisphere (Magnuson et al. 2000; Benson et al. 2012). The variability acts as noise that can make the signal, climate warming, impossible to detect from relatively short time series of 5 to perhaps even as long as 30 years.

Our study has made a significant advance in accounting for the multitude of components producing the residual variability around long-term linear trends. The variation explained by linear trends alone is approximately 7 %. In this study, we have increased the amount of variation explained (ca. 59 %) by including a suite of explanatory variables including *daily* weather, *winter* weather, and *cycles*, long-term climate drivers, and solar activity. Providing these analyses of the residual variation around the linear trends associated with a warming climate contribute to clarifying the difference between long-term climatic change from inter-annual and inter-decadal variation at a variety of time scales.

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