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Wintertime weather-climate variability and its links to early spring ice-out in Maine lakes

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Abstract

In recent decades, Maine lakes have recorded their earliest ice-out dates in over a century. In temperate regions, seasonal lake ice-cover is a critical phenomenon linking climate, aquatic ecosystem and society. And the lengthening of the ice-free period due to warmer climate has been linked to increased algal growth and declining lake water quality, warming of water temperatures leading to alterations in aquatic biodiversity, and the shortening of ice-fishing period and other traditional winter activities over lakes. In this study, historical record of eight lakes and six benchmarked meteorological stations in Maine for the period 1950–2010 were analyzed to (1) investigate the relationship between antecedent winter (January–February) temperatures, degree-day variables, and spring-time ice breakup dates, including the identification of thresholds and (2) determine the influence of the extreme phases of select atmospheric teleconnection patterns (Tropical Northern hemisphere- TNH and North Atlantic Oscillation- NAO) on the winter degree-day quantities and spring ice-out dates. The influence of antecedent winter degree-days on spring ice-out dates was characterized by determining the threshold winter accumulated freezing and melting degree-day (AFDD and AMDD), the exceedance (non-exceedance) of which engenders early (late) spring ice-out dates. Statistical analysis between teleconnection indices and winter AFDD and/or AMDD quantities for Maine revealed an asymmetric relationship. Strongly negative phases of TNH and, to a lesser extent, positive phases of NAO are linked with spatial and temporal pattern of early spring ice breakup events in Maine lakes. These relationships taken together with observed warming trends have the potential to accelerate the decline in water quality in Maine lakes.

In the spring of 2010, a number of lakes in Maine, a state situated in the northern New England region of the United States with over 5500 lakes, recorded their earliest ice-out dates (a term used interchangeably with ice breakup/ice-off/ice thawing date in this study) in over a century (Bayly 2010). This resulted in the hasty enactment of a new open-water fishing season Bill and cancellation of major ice-fishing derbies throughout the state. Furthermore, the early end to annual ice-season raised fears that the water quality in Maine lakes will plummet stemming from algal blooms and shortening of the annual clear water phase, as studies have shown that the lengthening of the ice-free period in temperate and Arctic lakes directly and indirectly promotes algal growth (e.g., Adrian et al. 1999; Prowse et al. 2011). With increases in urbanization and associated nutrient loading in lakes being projected for various regions in Maine, the effect of late-winter/early-spring lake ice-off events on the ecological and social systems linked to Maine's lakes promises to be more severe. These issues thus necessitate detailed climatological analysis to understand the potential drivers of early spring ice out events in Maine lakes.

The nature of attendant variability and change in the timing of lake ice out merits an assessment of the individual and joint effects of climatic variability and change. In Maine, only modest monotonic trends towards early ice-out are observed, however, as noted by Hodgkins et al. (2002), recent decades show appreciable change gleaned from decadal scale smoothing analysis towards early ice-out. It was also noted that these changes in ice-out dates correspond to 1.4–1.5°C change (over a 150 yr record) in the mean spring (March–April) temperatures over the New England region. On interannual time scales, this study shows that there is significant year-to-year swing in the timing of ice out dates in Maine lakes. Furthermore, the chain of events that modulate lake phenology involve interlinked large-scale

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

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atmospheric circulations, weather patterns, and warm and cold spells that accelerate or impede the lake ice-in buildup and melt. For example, the winter of 1983, a strong El Niño year in the tropical Pacific, was characterized by a persistent above normal surface pressure anomalies over eastern Northern American regions. This resulted in the mean winter air temperature over lake Sebec to rise by 2.5°C (1.3σ), which in turn resulted the lake to experience spring ice out 9 d (1.2σ) earlier than the median ice out date for the period 1950–2010. This exemplifies that the role of interannual large-scale atmospheric circulation patterns (teleconnections) on the variability of lake ice out date in Maine is strong and thus must be properly characterized in the context of the observed changes in lake ice phenology for the region. Furthermore, due to their gradual evolution, persistence and oscillatory behavior, large-scale teleconnection patterns have the potential to (1) offer seasonal and longer time scale predictability of ice breakup dates, premised on appropriately derived variables, (2) alter the temporal pattern of variability of lake ice out dates through long term changes in the frequency and amplitude of coupled oceanic atmospheric processes, such as El Niño-Southern Oscillation (ENSO), which have undergone significant changes in recent decades.

Few regional ice phenology studies have examined the linkages between ice breakup/freeze up dates, local climate and large-scale atmospheric/oceanic oscillations in North American and European (e.g., Anderson et al. 1996; Bonsal et al. 2006; Sánchez-López et al. 2015) lakes. For instance, a recent study by Sánchez-López et al. (2015) found that North Atlantic Oscillation (NAO) pattern affects the timing of ice breakup in Spanish alpine lakes through its influence on one or more climate variables during winter and early spring. In most of these studies, correlation or other linear analysis method is employed to determine the strength of association between atmospheric/oceanic oscillations, local climate variables and ice phenology. However, given that (1) the influence of teleconnection patterns on local climatic variables is asymmetric (Hoerling et al. 1997; Rodionov and Assel 2000) (2) the relationship between local climatic variables (e.g., temperature, snowfall, precipitation) and lake ice processes is nonlinear (Ashton 1986; Leppäranta 2010; Leppäranta 2014), a fuller exposition of the interrelationships between weather-climate and lake variables as they induce variability and change in lake ice phenology is still less understood. While large scale teleconnection patterns have been shown to have linear relationship with ice-out dates, perhaps a more systematic characterization warrants identification of thresholds in climate variables (e.g., accumulated degree-days) whose exceedance or non-exceedance may lead to large shifts in the ice-out dates or what is often termed as no complete ice cover on lakes.

The timing of lake ice breakup date is strongly modulated by temporally (and in some cases spatially) integrated thermal fluxes at the surface of ice-cover, which in turn is determined by prevailing meteorological conditions and limnological factors during the ice cover season. As such the role of seasonal thermal forcing on the lake ice-system is nonlinear and involves thermal thresholds. A number of studies have established that local air temperature is related to various thermal fluxes over lake ice and therefore can reasonably explain the variation in ice off dates (e.g., Stankiewicz 1947; Livingstone 1997; Hodgkins et al. 2002). For New England lakes, Hodgkins et al. (2002) also showed the existence of a significant ($p < 0.05$) correlation between the historical spring ice out dates and spring (March–April) temperatures. However given that (1) the timing of ice-out events in New England lakes is shifting towards early spring dates, and (2) the natural and/or anthropogenic forced climate warming is projected to continue for the Northeast region (IPCC et al. 2007) which sets the winter period to provide the bulk of the thermal energy to form and thicken the ice cover over lakes, it is imperative that the relationship between spring time ice-out dates and antecedent winter temperatures including thresholds be characterized so as to anticipate the timing of early spring ice breakup dates.

The primary focus of this article is thus to characterize the role of antecedent winter teleconnections, with origins in the tropical oceans, in driving early spring ice breakup events in Maine lakes, where ice-out dates have been studied from the standpoint of long-term trends, yet empirical diagnosis of linkages between lake ice-out dates, antecedent winter temperatures and teleconnection patterns has not been pursued. Thus the three objectives of this study are:

1. Analysis of the leading pattern of anomaly in the ice-out dates of Maine lakes.
2. Characterization of the link between spring ice out dates and antecedent winter temperatures (and derived degree-day variables) including the identification of thresholds within seasonal winter temperatures whose exceedance/non-exceedance engenders anomalous ice breakup events.
3. Quantification of the influence of select large-scale atmospheric circulation patterns, that operate at interannual time scale, on the winter degree-days quantities and lake ice breakup dates in Maine.

Study site and background

Study site

Maine has such climate diversity that the climate spectrum found in only three degrees of latitude in Maine occurs over 20° of latitude in Europe (Jacobson et al. 2009). Based on monthly average temperatures and precipitation data from 1895 to 2007, NOAA's National Climate Data Center broadly classifies Maine into three climate divisions: Northern, Southern interior and Coastal. The Northern division of Maine experiences some of the lowest temperatures and highest snowfalls in the eastern United States during winter and early spring while strong maritime influences keep the the climate mild along the coastal division. (Lautzenheiser 1972; Jacobson et al.

2009). Annual mean temperature in the Northern region is 4.4°C while in the Southern regions and Coastal regions are 6.7°C and 7.8°C, respectively.

In Maine, winter season (short days, heavy snow-fall, and freezing temperatures) begins in earnest after the December equinox. Most inland regions will reach their lowest temperature around mid-January whereas coastal areas tend to reach their minimum temperature values around the last week in January or first week of February (Zielinski and Keim 2003). It is also during this time of year that complete ice cover forms on lake surface in Maine. The winter season extends until March and after the March equinox spring season officially begins. Ice cover usually disappears from lakes during the months of April and May. Hence in this article, winter is exclusively used to refer to January and February while spring refers to March and April. Based on the correlation analysis shown in Supporting Information Appendix A, no significant correlation exists between winter and spring temperatures. This indicates the presence of independent climate drivers for the two seasons and that the contribution of winter and spring temperatures on ice-out in Maine lakes is to a large extent independent.

Lake ice cover dynamics

Lake ice cover formation, growth and melt rates are outcomes of an energy balance at the surface of lake (e.g., Ashton 1986; Leppäranta 2010), which can be written as

$$\Phi_N = \Phi_{sw}(1-\alpha)(1-\beta) + (\Phi_{L\downarrow} - \Phi_{L\uparrow}) - \Phi_E - \Phi_S + \Phi_p \qquad (1)$$

where Φ_N = net energy at surface, Φ_{sw} = incident short wave radiation, α = surface albedo, β = fraction that penetrates surface, $\Phi_{L\downarrow}$ = incoming long wave radiation, $\Phi_{L\uparrow}$ = outgoing long wave radiation, Φ_E = latent heat flux, Φ_S = sensible heat flux and Φ_p = heat from precipitation. However, explicitly calculating Φ_N using Eq. 1 requires detailed information on various environmental and lake parameters such as surface albedo, long and short wave radiation, snow/ice density, wind speed which are often not available at weather stations near lakes. Analytical studies on ice often employ degree-day methods for a first order approximation of the bulk growth and melt rate of ice over a period based on the physical basis that air temperature strongly relates to sensible heat flux, net long wave radiation and to a certain extent latent heat flux over lake/ice cover surface (Ashton 1986; Leppäranta 2010). The most basic of the degree-day formulation used is given as:

$$\mathrm{AFDD} = \sum_{i=1}^{i=n} (T_0 - T_i)\Delta t, \quad T_0 > T_i \qquad (2)$$

$$\mathrm{AMDD} = \sum_{i=1}^{n} (T_i - T_0)\Delta t, \quad T_i \geq T_0 \qquad (3)$$

where AFDD = accumulated freezing degree-days, AMDD = accumulated melting degree-days, T = air temperature and T_0 = base temperature. The time interval Δt is usually chosen as one day. Although the base temperature T_0 can vary depending on physical, meteorological and atmospheric conditions over lakes, it is often taken as 0°C (32 °F). The basic assumption in Eqs. 2 and 3 is that AFDD represents a negative net radiation at surface, meaning the lake is losing heat energy to the atmosphere while AMDD signifies a positive net radiation at surface indicating the lake is gaining heat energy from atmosphere. For further details on the different analytic models that couple lake ice growth and melt with accumulated degree-days and/or their underlying thermodynamic principles, the reader is referred to a book by Leppäranta (2014) and articles by Ashton (2011) and Leppäranta (2010).

Teleconnection patterns

Teleconnection patterns in atmospheric and climate sciences, refer to quasiperiodic and persistent anomalies in the atmospheric pressure and circulation pattern that span over large geographical areas (Nigam 2003; Chase et al. 2005). These patterns are primarily outcomes of the internal dynamics in the atmosphere although some teleconnection patterns have been shown to be sensitive to particular sea surface temperatures. Using correlation and rotated principal component analysis, a number of atmospheric/oceanic teleconnection patterns have been identified (e.g. Barnston and Livezey 1987, Nigam 2010).

There may be several atmospheric/oceanic teleconnections originating in the Atlantic and Pacific that influence Maine's winter climate. However given that (a) the main focus of this study is on extra-tropical winter teleconnection patterns that operate at inter-annual time scale (b) the seasonality, evolution and persistence in many of these oceanic/atmospheric teleconnections are still less understood, we selected only two major mid-latitudinal winter teleconnection patterns for further analyses, which are discussed below. For interested reader, additional analyses on the atmospheric/oceanic patterns that may influence winter temperature variability in Maine are presented in Supplementary Section 2.

The **Tropical/Northern Hemisphere** (TNH) is a prominent wintertime (November-February) teleconnection pattern with primary center of action over the Pacific northwestern coast of the United States and a separate center of action of opposite sign over the Hudson Bay. A weaker center of action, having same sign to that of the Pacific center also extends across southeastern Mexico and Cuba (Barnston and Livezey, 1987). According to NOAA's climate prediction center, fluctuation in TNH indices represent large-scale departures both in the amplitude and location of the climatological mean Hudson Bay trough and also position and eastward extension of the Pacific jet stream.

For the New England region of the United States, monthly or seasonal TNH indices reflect the atmospheric circulation pattern upwind of the region. For instance during pronounced negative TNH phases, the trough over Hudson Bay is abnormally weak and is located further north from its mean position resulting in northward shifted, zonally oriented polar jet stream. Such flow pattern enhances flow of marine air from the Atlantic and prevents the accumulation of dry frigid air over the New England region causing warmer winters (see Appendix C).

TNH variability is sensitive to strong ENSO forcing although it is largely driven by the inherent atmospheric dynamics within the extra-tropics. Circulation patterns during pronounced negative phase of TNH have been closely correlated with that of strong El Nino episodes (Barnston et al. 1991; Trenberth et al. 1998). El Nino is predictable on a seasonal-to-interannual and longer time scales (e.g. Ramesh & Murtugudde 2012; Hoskins 2013).

North Atlantic Oscillation (NAO) is a dominant mode of atmospheric circulation pattern in the North Atlantic with low pressure center over Iceland and high pressure center over subtropical North Atlantic (Azores). Its indices reflect the pressure gradient across the North Atlantic and change in the intensity and location of the North Atlantic jet stream, which affects heat and moisture transport the adjacent land and ocean (Hurrell 1996).

NAO is strongly related to the leading structure of variability of wintertime sea level pressure (SLP) over the Northern hemisphere, the Arctic Oscillation (AO) (Thompson and Wallace 1998). The maps between the two modes of variability are almost indiscernible (except for the Pacific region) and correlation between their monthly indices exceeds 0.7 (Deser 2000). There are many studies that argue that AO and NAO are regional expression of the same phenomenon (e.g. Wallace 2000; Marshall 2001) and the debate over NAO and AO as single or separate physical entities is still ongoing. Thus we restrict our focus in this study to the impacts of NAO patterns on the variability of winter temperatures and ice out dates in Maine despite the fact that AO patterns may influence Maine's winter climate and lake ice season.

While TNH patterns describe the change in the atmospheric circulation upwind of the New England region, NAO reflect the circulation on the downstream side. During pronounced positive NAO phases, the pressure gradient in the North Atlantic is unusually strong causing the polar jet stream to be zonally oriented and to shift further north. These conditions allow the influx of modified Pacific air into New England which in turn produce warmer winters and lesser snow storms (Zielinski and Keim 2003). In contrast during negative NAO phases, above normal height anomalies develop over Greenland generating a blocking pattern over the North Atlantic and strengthening of the East coast trough (Hartley and Keables 1998; Bradbury et al. 2002, Zielinski and Keim 2003). These conditions cause the polar jet stream to be meridionally oriented and to shift further south which in turn advances the buildup of cold air and snow storms into New England.

The primary mechanism for NAO variability is thought to be the internal dynamics within the north Atlantic atmosphere (Marshall et al. 2001). Atmospheric variability has little or no temporal persistence due to its chaotic nature, which limits the predictability of NAO at sub-seasonal to inter-annual time scale. However, recent studies have demonstrated the link between winter AO pattern and preceding summer Arctic sea ice and fall land snow cover can provide long-range (weeks in advance) predictability of winter AO/NAO (Cohen and Jones 2011; Handorf et al. 2015). Furthermore, a few studies have shown that there is an association between sea surface temperatures in the tropical Pacific/North Atlantic and winter NAO and this promises to enhance the predictability of NAO in the Atlantic basin in the future (Hoerling et al. 2001; Kushnir et al. 2006).

Method

Historical observations of lake ice out dates in Maine

Lake ice-out date refers to the time when ice-cover completely clears from a lake (Hodgkins et al. 2002). For the study period (1950–2010), serially complete ice out data for the selected eight Maine lakes were obtained from a USGS publication (Hodgkins 2010) and from website publication by the Department of Conservation for the state of Maine (http://www.maine.gov/doc/parks/programs/boating/ ice_out12.html). Geomorphological detail of the selected eight lakes is provided in Table 1.

Local winter temperature and derived metrics

The daily mean temperature data from January to April for different regions in Maine were obtained from local United States Historical Climatology Network (USHCN) stations. Data from USHCN stations was preferred as it imposes genuine quality assurances and quality control checks (Karl and Williams 1987; Quayle et al. 1991). It is necessary that the station data used have nearly complete daily temperature data for the study period in order to study the link between seasonal winter degree-days and lake ice-out dates/teleconnection patterns. Thus in this article, a year is considered missing if it does not contain temperature data for at least 75% of the winter days (January–February). Furthermore, a station is used only when a station has daily temperature data for at least 55 yr out of possible 61. Therefore out of the available twelve USHCN stations in Maine, only six are used. At each of these stations, the accumulated freezing (melting) degree days during winter were calculated as the daily degree days below (above) 0°C summed over the total number of days during winter the daily average temperature was below (above) freezing.

Table 1. Geomorphological data on selected Maine lakes.

Lakes	Longitude	Latitude	Area ($\times 10^6 m^2$)	Mean depth (m)	Elevation (m)
China	69.55	44.43	15.94	8.53	60
Damariscotta	69.48	44.18	18.96	9.14	17
Maranacook	69.96	44.33	7.46	9.14	64
Moosehead	69.67	45.64	305.42	17.07	313
Mooselmeguntic	70.81	44.91	66.2	18.28	447
Rangeley	70.70	44.94	25.5	18.28	463
Sebec	−69.23	45.26	25.74	52.1	98
West grand	−67.84	45.24	58.54	11.28	91

Gridded winter climate and sea surface temperature anomalies

Long term (1950–2010) gridded monthly 500 mb geopotential heights, sea and land surface temperatures and wind speed data for January and February were retrieved from National centers for environmental prediction (NCEP) reanalysis dataset (Kalnay et al. 1996). These monthly metrics were later averaged and their climatological (1950–2010) mean removed to create gridded winter climate and sea surface temperature anomalies dataset.

Historical winter TNH and NAO indices

The January and February monthly indices for TNH and NAO patterns during the study period (1950–2010) were obtained from NOAA's National Center for Climate Prediction (ftp://ftp.cpc.ncep.noaa.gov/wd52dg/data/indices/tele_index.nh). These monthly indices were later averaged to compute the mean winter indices of the selected circulation patterns.

Kernel density estimation

It is a well known nonparametric method for estimating (in any number of dimensions) the probability density function of a random variable based on a random sample (Silverman 1986; Scott 1992). It entails the construction of a window of certain width h and fitting of a symmetric probability density function $k(\cdot)$ (e.g., Gaussian, triangular, Epanechnikov) to the observation in each window (Silverman 1986). The estimated density for any value is simply the sum of estimates from the density function of each window. For n number of available data point with d-dimensions of vector x, the multidimensional probability density function $\rho(x, h, n)$, is estimated by centering preferred kernel function k and scale h at each data point X_i

$$\rho(x,h,n) = \frac{1}{nh^d}\sum_{i=1}^{n} k\left(\frac{x-X_i}{h}\right) \tag{4}$$

The attractive feature of this technique is that the probability density function used is local and hence not globally affected by outliers. Also since it makes weak prior assumption of the underlying probability density function, it is data driven, robust and portable across datasets although not efficient in extrapolating beyond extreme values. For more details on the topic of univariate and multivariate kernel density estimation, refer to Silverman (1986) and Scott (1992).

In this study, Gaussian kernel is used to develop probability density estimates for (1) characterizing the threshold degree-days above/below which are associated with the earliest and latest 15 ice out dates for the eight studied lakes, (2) assessing the change in the empirical probability density of winter density of degree-days during different phases of TNH and NAO. Furthermore, Silverman's reference bandwidth method—which is the most popular and practical technique of estimating the global bandwidth h for Gaussian kernels (Sheather 2004)—was used for estimating the optimal bandwidth h_{opt}

$$h_{\text{opt}} = \frac{0.9\boldsymbol{\sigma}}{n^5} \tag{5}$$

where $\boldsymbol{\sigma} = \min(s, R/1.34)$ where $s^2 = \frac{1}{n-1}\sum_{i=1}^{n}(x_i - \bar{x})^2$ and R is the interquartile range of the data.

Bootstrap method

It is a nonparametric technique introduced by Efron (1982) that is used extensively in carrying out test of hypothesis or estimation of the sampling distribution of some statistics by either constructing confidence interval or attaching standard error to an estimate. This method is particularly useful when analyzing data for which the distribution is unknown or when random sampling from a population is not possible due to small sample size. The sampling distribution is determined empirically by randomly resampling with replacement from the original sample, with the same original sample size. The desired statistic and its distribution can be determined from each bootstrapped sample and the distribution of each statistics. For more details on the bootstrap method, the reader is referred to Efron (1982).

In this study, 10,000 bootstrap replication of size n are generated from the historical data of studied lakes to generate an empirical probability distribution when subsample size is less than 30. The $(1-\alpha) \times 100\%$ confidence intervals for bootstrap estimates are obtained using the percentile method. That is, the two end points of the $n_b = 10{,}000$ bootstrap distribution are taken at the $(\alpha/2)$ 100^{th} and $(1-\alpha/2)$ 100^{th} percentiles.

Principal component analysis

As a method for reducing the dimensionality of a dataset containing of a large number of inter-related variables, principal components analysis (PCA) has found wide spread use in the fields of hydrology and atmospheric sciences (Wilks 2011). The reduction in dimensionality is attained by projecting the original variables onto the eigenvectors of the spatial cross-correlation (covariance) matrix of the variables. This results in a new set of orthogonal variables (patterns) called principal components (PCs) that are (1) linear combination of the original variables, (2) uncorrelated with each other, (3) able to retain maximum possible fraction of the variance in the original data using fewer patterns. The PCA solution also yields eigenvalues, which describe the variance explained by each PC and eigenvectors (loadings), which basically express the association between the PC and the original variables. For more details on the topics of principal component analysis, reader is referred to a book by Jolliffe (2005) and Wilks (2011).

In this study, principal component analysis was applied on the (1) ice out date of eight lakes, (2) the winter degree-days (AFDD and AMDD) of six USHCN stations to determine the leading variability patterns that represents the historical variation in ice out date and winter degree-days in Maine. Three results are obtained from PCA solution: the principal components, which are time series of ice out dates/winter degree-days; the amount of variance explained by the PCs and the spatial pattern or loadings associated with the PCs.

Results

Statistics of early/late ice-out events in Maine

Figure 1b depicts the earliest 10 ice-out years for each of the eight Maine lakes from 1950 to 2010. While these lakes are found in different climate divisions (*see* Fig. 1a), approximately 70% of the earliest ice-out years were common to three or more of these lakes (*see* Fig. 1b). This temporal synchrony in the earliest ice-out years indicates that there is strong coherence among Maine lakes in their pattern of early ice-out dates. Furthermore, approximately 75% of the earliest ice-out years occurred after the 1970s suggesting that recently there is an increased tendency in these lakes to experience early ice-breakup dates.

To succinctly express the role of interannual winter climate variability in the context of extreme ice-out date patterns in these lakes, the unconditional probability distributions of the earliest and latest 10 ice breakup events for each of the eight lakes during randomly chosen 15 yr was compared with that of the frequency for (1) the last 15 yr of the most recent period (1996–2010), (2) the 15 yr when the average winter TNH index was in its lower quartile ($TNH \leq 0.47$), (3) the 15 yr when the average winter NAO index was in its upper quartile ($NAO > 0.2$). Out of possible 80, 39 of the earliest 10 ice breakup events for the eight Maine lakes occurred during the last 15 yr of the study period (1950–2010) representing at 97^{th} quantile of the unconditional distribution (*see* Fig. 1c). Furthermore, only 10 out of the possible 80 latest ice-out events occurred during these years, which is at the 10^{th} quantile. This is a reflection of the observed pattern in the timing of the mean ice-out date towards earlier dates for New England lakes, which has been described in detail by Hodgkins et al. (2002). However, 41 out of the possible 80 earliest ice-out events also occurred during the 15 yr when the average winter TNH index was at its lower quartile for the study period (*see* Fig. 1c). What makes this result interesting is that only three out of the 15 yr, when winter TNH in its pronounced negative phase, were post 1996. This in turn suggests that there is relatively modest influence of the recent "pattern" or trend in the earliest ice breakup events on the results for TNH events. Yet the mechanisms by which seasonal winter weather/climate variability preconditions lake ice cover towards early ice breakup dates in Maine is poorly characterized and understood. Figure 1c also shows that 20 out of the possible 80 ten latest ice-out events also occurred during the 15 yr when TNH was at its lowest quartile, representing at 55^{th} quantile. On the other hand, 5 out of the possible 80 latest ice-out events (5^{th} quantile) and 19 out of the 80 earliest ice-out events (50^{th} quantile) occurred during winters when the average NAO was at his highest quantile (*see* Fig. 1c). These observational analyses indicates that (1) interannual variability is a significant determinant of extreme ice out dates, (2) winter teleconnection patterns such as TNH and NAO influence the timing and frequency of extreme ice breakup dates in Maine lakes.

For the sake of comprehensiveness, the major spatial and temporal pattern of variability of ice out dates in Maine lakes was investigated by applying PCA on the ice-out date of eight Maine lakes with serially complete data for the period 1950–2010. The first principal component (PC1) alone reproduces more than 80% of the total variance and therefore may be considered as the leading pattern of lake ice-out date variability in these lakes (see Supporting Information Appendix A). The homogeneity of signs in lake loading (correlation coefficients between the lake ice out dates and the PC) of PC1 reflects synchronous variation in all eight lakes although lakes near the coast display slightly higher loadings as compared with lakes found in the inlands (*see* Fig. 2b). The temporal pattern of PC1 shows a sequence of "strong" positive scores (corresponding to later than average ice-breakup dates in lakes) in the 1960s and 1970s that were later overtaken by a series of "strong" negative scores (signifying earlier than average ice breakup dates) since the early 1980s. Although no secular trend for PC1 time series was found (*see* Supporting Information Appendix A, Table B6), the sequence of PC1 scores is a reflection of the recent pattern of lake ice out date

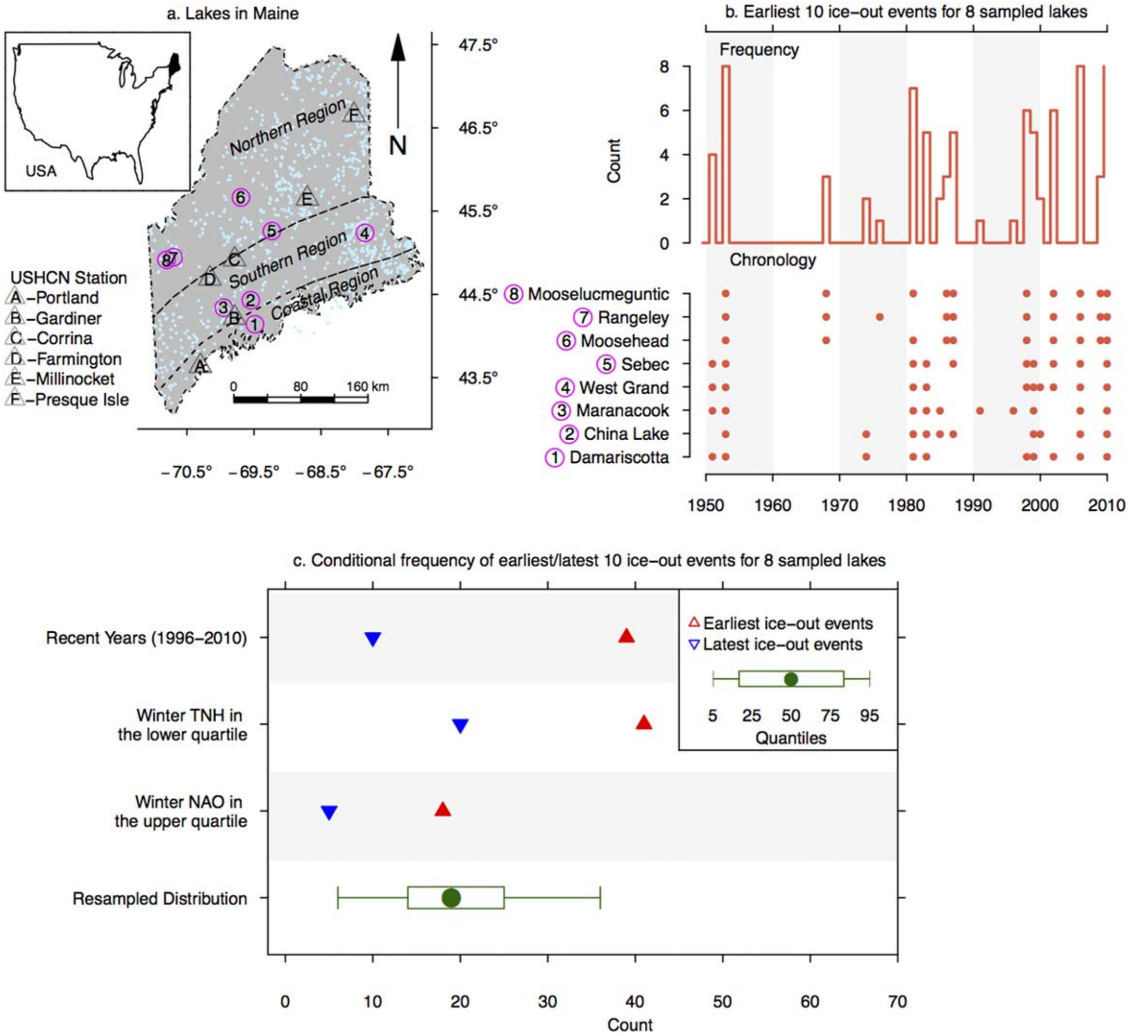

Fig. 1. Temporal pattern of the earliest/latest 10 ice-out years for each of the eight lakes in Maine from 1950 to 2010 and their unconditional/conditional distribution to winter climate variability patterns. (**a**) Location of lakes in Maine. The numbers inscribed in a circle and the alphabets inside a triangle represent the location of selected lakes and meteorological stations used for this study respectively. The cyan color dots represent the >5500 lakes in Maine. (**b**) Frequency and chronology of the earliest 10 ice out events. (**c**) Conditional frequency of the earliest/latest 10 ice-out events to winter climate patterns.

in Maine towards earlier dates (*see* Fig. 2a). Furthermore, the PC1 time series also shows high year-to-year fluctuation in ice out dates. This suggests that interannual variation in ice-out date has an important role on the timing of ice-off dates in these lakes. It should be noted that these observations apply to other Maine lakes as well as the PC1 times series for the eight lakes had a significant correlation ($|\rho| = 0.98,\ p < 0.05$) with the PC1 time series of 16 Maine lakes (*see* Supporting Information Section 1).

Linking ice-out dates to winter degree-day thresholds in Maine

The major temporal pattern of winter AFDD in Maine was examined by applying principal component analysis on the winter AFDD time series of six stations. The first principal component (PC1) represents 87% of the variability in AFDD in the six USHCN stations and thus may be considered as the leading pattern of winter AFDD variability in Maine (*see* Fig. 2c). The homogeneity of signs in station loading in PC1 reflects synchronous variation in winter AFDD in all stations (*see* Fig. 2b). Time series of PC1 (*see* Fig. 2c) shows high year-to-year variation in winter AFDD but no secular trend (*see* Supporting Information Appendix A, Table B6). Comparison of the PC1 of ice-out date and winter AFDD time series shows a significant ($|\rho| = 0.4,\ p < 0.05$) correlation between the PC1 of winter AFDD and ice-out date. This indicates that the timing of spring ice out date in Maine lakes is influenced by the variability of the preceding winter temperature.

Appropriate characterization of the link between spring ice-out dates and antecedent winter temperature further

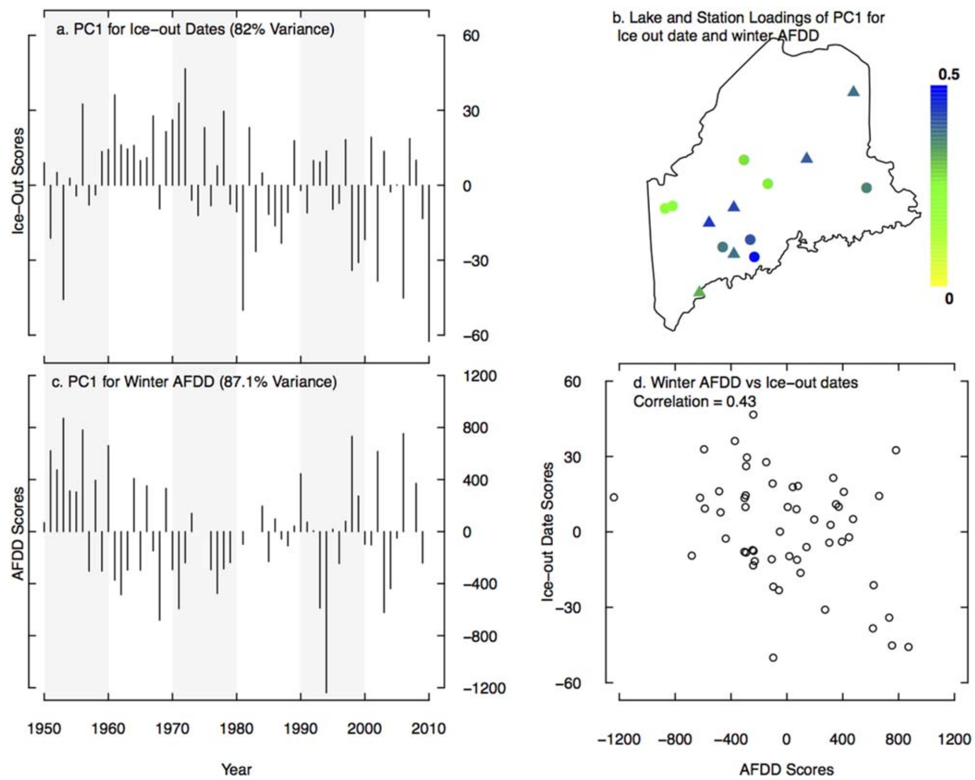

Fig. 2. The time series and loadings for the first principal component (PC1) of lake ice out dates and winter AFDDs in Maine for the period 1950–2010. The PC1 of lake ice out date corresponds to the major temporal pattern of ice out date for eight lakes while the PC1 of winter AFDD represents the major temporal pattern for winter AFDD in the five USHCN stations. (**a**) Time series of PC1 for set of eight Maine lakes. This PC retains 82% of their total variance. (**b**) Lake and station loadings of PC1 for lake ice out dates and winter AFDDs. Lakes (stations) are symbolized as circles (triangles). (**c**) Time series of PC1 for winter AFDD in the five stations. It contains 87.1% of the total variance in winter AFDD for the six stations. (**d**) Plot of PC1 of ice out dates (for eight lakes) as a function of PC1 of winter AFDD. Correlation between the two is 0.43 ($p < 0.05$).

clarifies the role of local winter temperature variability on the timing of spring ice breakup. Initially, the general relationship between spring ice out and winter degree-days in Maine was investigated using Pearson's correlation tests. Results show there is a significant ($p < 0.05$) positive correlation between local winter AFDD and ice-breakup dates of selected Maine lakes; that is, lower winter AFDD quantities are associated with early ice out dates and vice versa. Seasonal AFDD quantities explain 15–20% ($p < 0.05$) of the total variability in ice-out dates (*see* Supporting Information Appendix A). No systematic regional difference exists in the correlation coefficients between winter AFDD and lake ice out dates although there is considerable difference in the quantity of winter AFDD between stations and the variability and timing of lake ice breakup dates in the three climate regions of Maine. On the other hand, seasonal winter AMDD shows significant ($p < 0.05$) negative correlation with the spring lake ice-off dates indicating that higher AMDD magnitudes are linked to earlier ice out dates and vice versa. Winter AMDD quantities account for 10–28% ($p < 0.05$) of the total variability in the lake ice thawing dates (*see* Supporting Information Appendix A). Furthermore, there is an inland-coastal gradient in the correlation coefficient between AMDD and lake ice out date of lakes suggesting that for those lakes near the coast such as Damariscotta or China lake, the occurrence and magnitude of the nonfreezing winter days (AMDD) has stronger effect on the ice-off dates than that of lakes found deep in the interior (Rangeley, Mooselmeguntic).

Visual inspection of the relationship between winter temperatures (degree-days) and ice-out dates of selected lakes reveals that ice-out dates in Maine have higher sensitivity to warmer winter temperatures (lower AFDD and higher AMDD) than colder ones. This is due to the fact that ice-cover produced during warmer winters requires relatively lower thermal forcing to melt in spring as compared with those produced during colder winters and thus is less affected by meteorological conditions in spring. This explains for the modest correlation results between winter temperatures and ice out dates as correlation tests can only gauge the average linear relationships. Furthermore, it reveals that simple linear models provide somewhat partial characterization of the threshold winter degree-days above/below, which engenders anomalous spring ice breakup dates in spring in lakes. However,

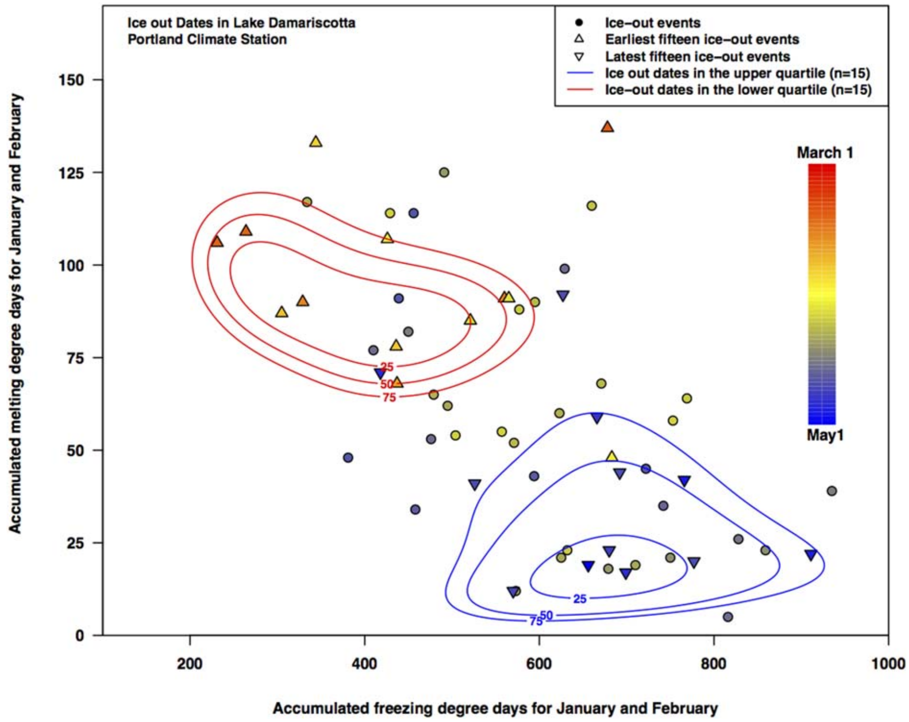

Fig. 3. Joint probability density of winter AFDD and AMDD for the earliest and latest 15 (upper and lower quartiles) ice breakup dates at lake Damariscotta. The Winter AFDD and AMDD at lake Damariscotta is calculated based on daily temperature data available at the nearby Portland station. The density contours are generated using nonparametric kernel density estimators. The red (blue) density contours represent the joint probability distribution of winter degree-days for the earliest (latest) 15 ice-off dates. The filled triangles denote the earliest or latest fifteen ice out dates while the dots represent the rest of the ice-out dates at lake Damariscotta.

nonparametric kernel density estimation method would be better suited to derive the existing relationship between ice breakup dates and antecedent winter degree-days as it makes no priori assumptions about such association or distributions. Thus to develop the relationship between variability in spring ice breakup dates especially the anomalous ones to antecedent winter temperatures, the joint density contours of the seasonal winter AFDDs and AMDDs for the earliest and latest 15 ice-out dates for selected lakes were generated using nonparametric kernel density estimators.

The red and blue contours in Fig. 3 show the joint probability density estimates of preceding winter AFDD and AMDD quantities for the earliest and latest ice-off events in spring respectively. It can be observed that more than 75% of the earliest 15 ice-out events at Lake Damariscotta occurred when the winter AMDD quantity was over 35° days centigrade (DDC) while nearly 75% of the latest 15 ice-out events had winter AFDD values below 325 DDC. This separation in AMDD and to a lesser extent AFDD quantities imply the presence of winter degree-day thresholds above/below which precondition the ice cover formed during winter to bring about early spring ice out dates in lake Damariscotta. Other lakes also show the presence of winter AFDD and AMDD thresholds that precede early/late spring ice out events (*see* Supporting Information Appendix B). Based on these results, it can be concluded that variability in spring ice-out events in Maine lakes is dependent on the exceedance/non-exceedance of the threshold degree-days during the antecedent winter.

Linking winter temperature variability to large-scale teleconnection patterns

The most relevant large-scale teleconnection patterns that influence seasonal winter degree-days quantities in Maine were identified by correlating the time series of PC1 for both seasonal winter AFDDs and AMDDs to the geopotential height at 500 mb (Supporting Information Appendix C). The time series of PC1 for AFDD have statistically significant ($/\rho/ > 0.4$, $p < 0.05$) correlations with the geopotential height anomaly time series over eastern North America and the Pacific Northwestern region of United States and Canada, which is reminiscent of the Tropical/Northern hemisphere teleconnection pattern (*see* Supporting Information Appendix C). In contrast, the time series of PC1 for AMDD show significant correlation ($/\rho/ > 0.4$, $p < 0.05$) with the geopotential height anomaly time series over Iceland and Atlantic Ocean, consistent with North Atlantic Oscillation (NAO) pattern. While the major thrust of this study is to understand the role of winter TNH and NAO patterns on spring ice breakup dates, results from ancillary analyses relating PC1 of winter degree days in Maine with global sea surface temperatures and upper air geopotential heights, and putative links to known oceanic/atmospheric modes of climate (such as Atlantic tripole, Atlantic multidecadal oscillation) are presented in Supporting Information Section 2.

Pearson's correlation tests between local temperatures (as recorded by stations) in Maine and average winter TNH indices show that TNH has a significant ($p < 0.05$) negative correlation with local winter temperatures (*see* Supporting Information Appendix A). That is, negative phases generally are associated with warmer winters (lower AFDD and/or higher AMDD) and vice versa. TNH patterns explain about 10–17% ($p < 0.05$) of the total variability in AFDD quantities recorded at all stations and 9–10% ($p < 0.05$) of the total variability in AMDD at Farmington and Corinna stations. The correlation coefficient between TNH and local winter degree-days also has an inland-coastal gradient with inland stations displaying higher correlation coefficients than that of the coastal.

Winter NAO patterns show significant positive correlations (at $p < 0.05$) with local winter temperatures in some of the southern and coastal stations (Portland, Gardiner, Farmington and Millinocket) (*see* Supporting Information Appendix A). The variance explained by NAO indices ranges from 10% to 19% of total AMDD variation recorded at these stations. No significant correlation between NAO phases and winter AFDD quantities was registered at any of the stations. The absence of a significant association between NAO and winter AFDD or mean winter temperature implies that NAO phases mainly influence the warm tail distribution of seasonal winter temperatures while having little or no effect on the mode or cold tail distributions of winter temperatures. Furthermore, partial correlation analysis indicates that the linear relationship between TNH (NAO) and temperature metrics is relatively insensitive to NAO (TNH) indices (*see* Supporting Information Appendix A).

A closer inspection of the composite geopotential heights patterns to opposing extreme phases of TNH/NAO shows asymmetry, and differences in the local amplitudes of the anomaly patterns for Maine (*see* Fig. 4a–d). The relative effect of this potentially "nonlinear" atmospheric response to strong TNH and NAO patterns on winter temperature variability in Maine was investigated by comparing their empirical density function of winter degree-days. The empirical density function during lower quartile TNH phases ($\mathrm{TNH} \leq -0.47$) shifts toward lower winter AFDDs as compared with the other phases ($\mathrm{TNH} > -0.47$) in all six stations (*see* Fig. 5 and Supporting Information Appendix D). Thus, the observed that TNH patterns affect the mode and lower tail of the seasonal winter temperatures distribution in Maine. This effect is exemplified in Fig. 5a–c where during lower quartile TNH phases (red line), there is a marked shift in the empirical density estimate of Portland's winter temperatures towards warmer degree-days (especially in AFDD).

On the other hand, it was noted that NAO patterns influence the warm tail of seasonal winter temperatures in southern and coastal regions as the empirical density function during upper quartile NAO phases shifts towards higher AMDDs as compared with other phases in most southern stations (*see* Fig. 5 and Supporting Information Appendix D). This effect is illustrated in Fig. 5d–f where during upper quartile NAO phases (red line), there is a strong shift in the empirical density estimate of Portland's winter temperatures towards warmer degree-days (especially in AMDD).

The observed effects of winter TNH/NAO variability on the statistics of winter degree days may provide prospects for spring ice out prediction in Maine premised on the probability that the threshold winter AFDD and AMDD quantities, that are associated with early and late spring ice breakup events of lakes, is exceeded. In this regard, Fig. 3 shows that 75% of the earliest 15 ice-out events in lake Damariscotta had winter AFDD below 325 DDF. During lower quartile TNH phases (upper quartile NAO phases), there is approximately 76% (63%) chance that the accumulated freezing degree-days at lake Damariscotta will be less than 325 DDC, which is approximately 80% (27%) more likely as compared with the other winter TNH (NAO) phases. This affirms that forecasts of TNH and NAO indices can be used in the season-ahead or longer prediction of early/late spring ice out events in Maine lakes premised on the exceedance probability of the threshold winter degree-days.

Teleconnection patterns and lake ice-off dates

The overall strength to which winter TNH and NAO patterns precondition spring lake ice-out dates in Maine lakes were determined empirically by comparing the median ice out date of the eight lakes during lower quartile TNH phases ($\mathrm{TNH} \leq -0.47$) and upper quartile NAO phases to the unconditional median ice out date for 15 randomly chosen years in the study period (*see* Fig. 6). During upper quartile winter NAO ($\mathrm{NAO} \geq 0.2$) years, the median ice-out date for most lakes showed shifts towards earlier dates. However these shifts were only significant ($p < 0.05$) in the coastal lakes (China and Maranacook). On the other hand during lower quartile TNH ($\mathrm{TNH} \leq -0.47$) years, all lakes including those found in the deep interior regions such as Rangeley and Mooselmeguntic, whose climatological median ice out date for the period in this study is in late-April to early-May period, displayed significant ($p < 0.05$) shifts towards earlier dates than the unconditional median ice breakup date. Similar results were obtained when the threshold for these teleconnection patterns were altered for different percentiles (*see* Supporting Information Section 3). These diagnostic analyses provide an empirical basis regarding the efficacy of pronounced negative TNH phase and pronounced positive NAO phase in bringing about shifts in the timing of ice breakup dates of Maine lakes towards earlier dates.

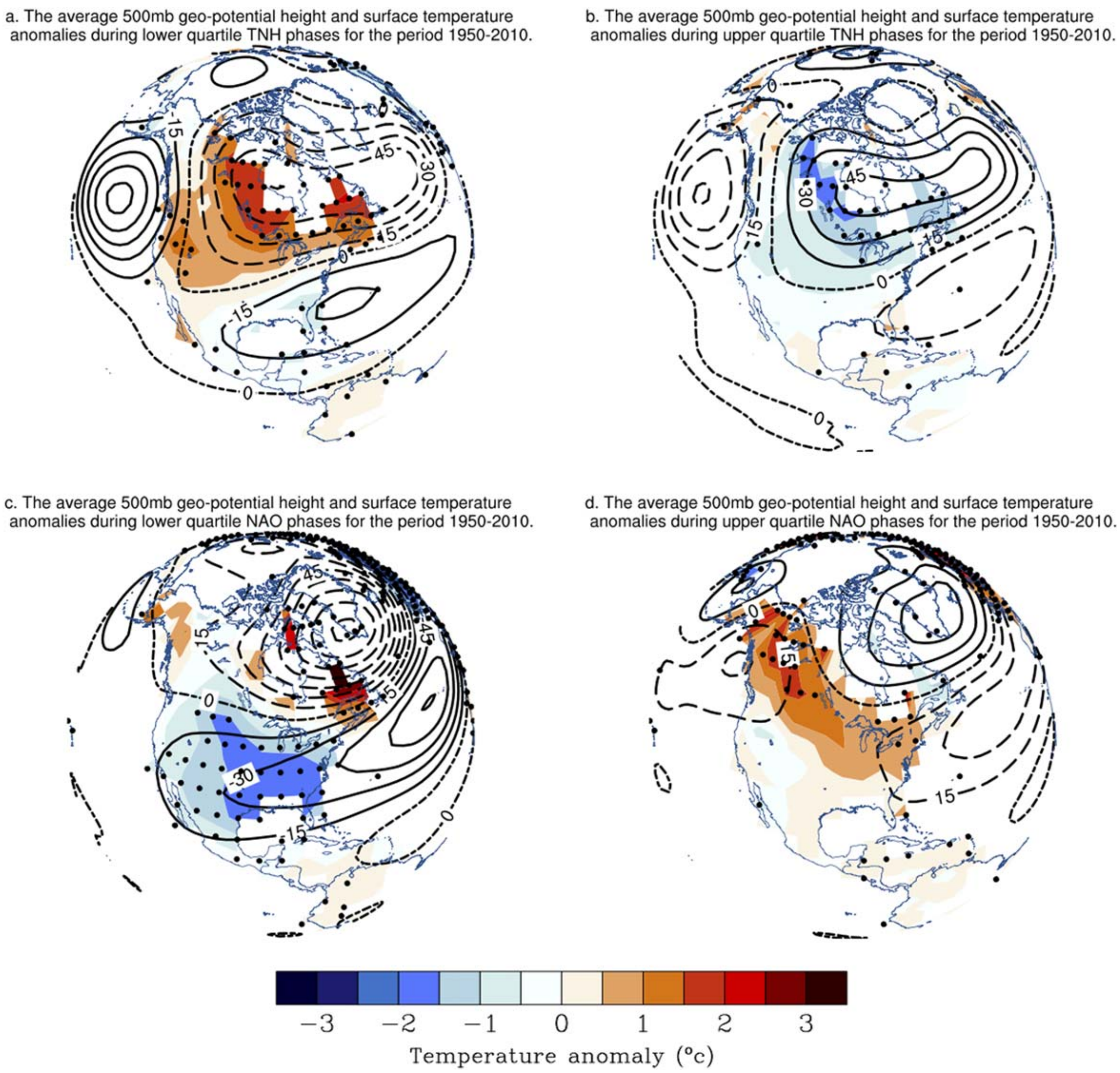

Fig. 4. Seasonal 500 mb geopotential height composites and surface temperature anomalies during lower quartile TNH phases (**a**–**b**) and upper quartile NAO phases (**c**–**d**) during winter for the period 1950–2010. The contours represent geopotential height anomaly at 500 mb while the colors represent the temperature anomaly at the surface. The dots represent grid points where the surface temperature anomaly is significant at $p < 0.05$.

Discussion

In this article, we studied interannual variability in spring ice out dates in Maine lakes and its association with preceding winter weather-climate variability. The influence of antecedent winter degree-days on spring ice-out dates of selected eight Maine lakes was characterized by determining the threshold winter accumulated freezing and melting degree-day (AFDD and AMDD), the exceedance (non-exceedance) of which engenders early (late) spring ice-out dates. Winter teleconnections such as TNH and NAO were determined to impact the timing of spring ice out dates in Maine through their influence on the winter degree-days. In closing, we offer the following observations, and discuss emerging research directions:

1. The results in this study show that significant season-ahead information regarding springtime lake ice-out resides within the wintertime temperature patterns for Maine lakes, even though the bulk of the ice-out date variability seems to be driven by spring temperature conditions. For the eight lakes, our correlation analysis indicates that spring (March–April) temperatures accounts for more than half ($p < 0.05$) of the total variability in the lake ice breakup dates for the study period (*see* Supporting Information Appendix A). However, linkages identified in this study between ice-out and wintertime weather and climate patterns are important for two other reasons: (1) recent early lake ice-out events in a number of southern and coastal Maine lakes signal a shift towards early spring (mid to late March) dates which

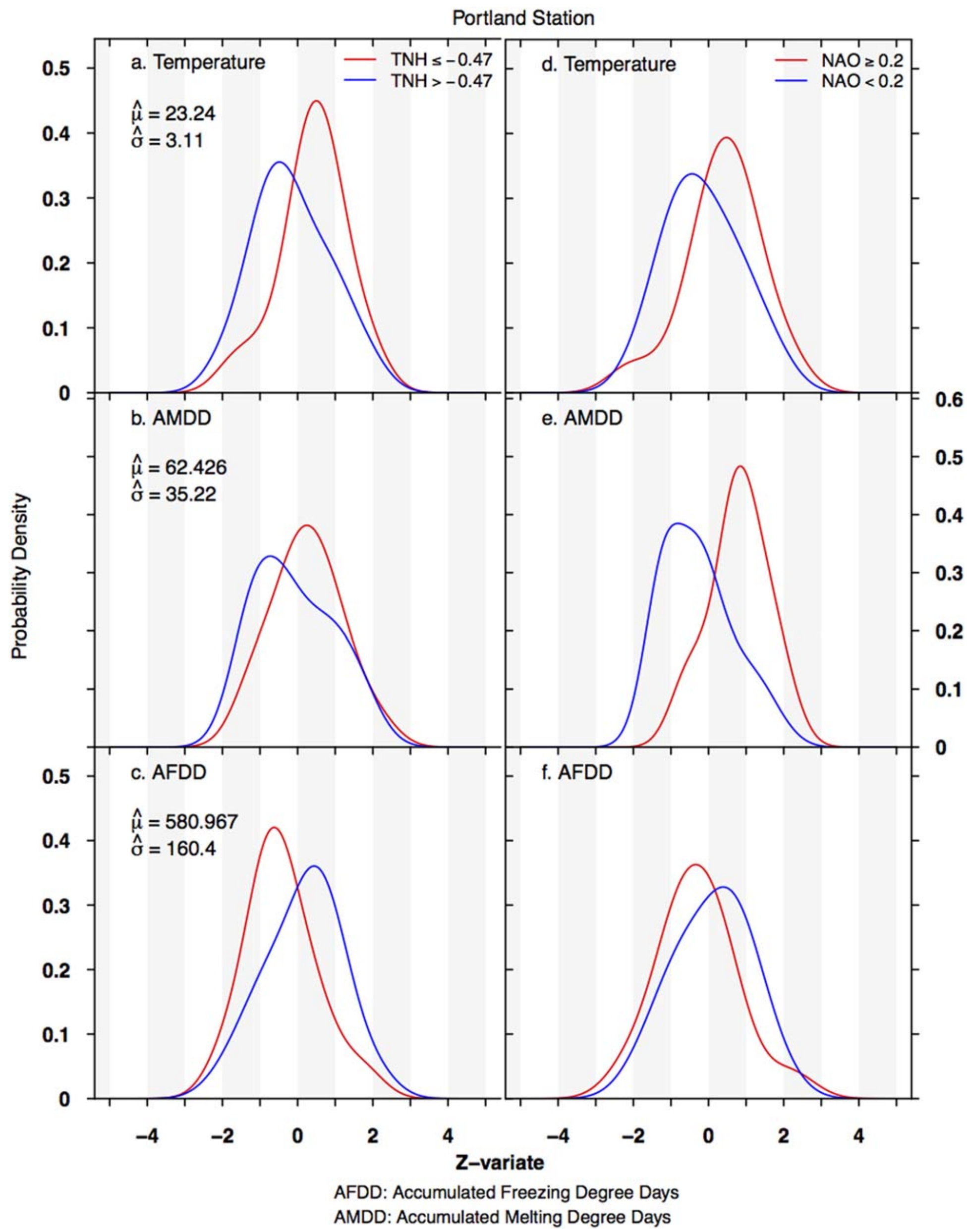

Fig. 5. Conditional probability density curves for Portland's winter temperature (and derived variables) during contrasting phases of (**a**–**c**) TNH (**d**–**f**) and NAO. The empirical probability density functions were constructed using nonparametric kernel density estimators. The red curves represent the conditional probability density function for Portland's winter temperatures (and derived variables) when (**a**–**c**) average winter TNH phase is in lower quartile (TNH ≤ -0.47) (**d**–**f**) average winter NAO phase is in upper quartile (NAO ≥ 0.2) while the blue curves denote the conditional probability density functions for winter temperatures when (**a**–**c**) average winter TNH index is not extreme negative phase (TNH > -0.47) (**d**–**f**) average winter NAO index is not extremely positive (NAO < 0.2).

reduces the role of spring climate conditions on early spring ice breakup dates and (2) the natural and/or anthropogenic forced climate warming is projected to continue for the Northeast region (IPCC et al. 2007) which sets the winter period to provide the bulk of the freezing energy to form and thicken the ice cover over lakes; it is imperative that the role of winter weather/climate variability on the ice-breakup dates of lakes in the Northeast regions be understood so as to anticipate major changes in the lake ice breakup regimes.

2. The majority of published research on lake ice phenology employ seasonal mean temperature as the choice of metrics for analyzing the link between local air temperatures and lake ice freeze up/breakup. The often-cited reason for such selection is that the use of degree-days over seasonal mean temperature does not improve regression/correlation results

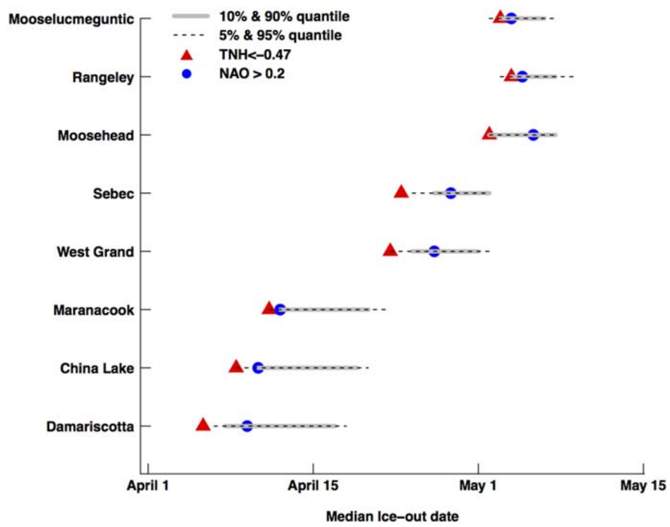

Fig. 6. The median ice out dates of eight selected lakes from 1950 to 2010 during lower quartile TNH phases (TNH $\leq$ 0.47) and upper quartile NAO phases (NAO $>$ 0.2). The variability band for the median ice out date of each lake was constructed using the bootstrap method. Solid lines show 10th–90th percentile range while dotted lines indicated confidence interval at 5th–95th percentile range. The filled triangles represent the median ice out date of each lake either during lower quartile TNH indices or upper quartile NAO indices.

(Livingstone 1997; Williams and Stefan 2006). However the determination of winter degree day thresholds that determine the timing of spring ice out in this study indicates that variability in seasonal and/or episodic temperatures are as important as seasonal mean temperatures in influencing lake ice phenology. Our correlation analyses also show that spring lake ice out in coastal/southern Maine lakes (such as Damariscotta and China lakes) was more sensitive to seasonal winter AMDD (warm tail of seasonal temperature) than seasonal mean temperature (*see* Supporting Information Appendix A). In addition to these results, the use of seasonal mean temperature is also less informative about the seasonal ice cover growth and melt processes that affect lake ice formation and duration. Thus we believe that future ice phenology studies should take into account the role of intraseasonal temperature variability on the interlinkages between seasonal temperature and ice cover duration.

3. The extensive use of linear regression/correlation in ice phenology studies has limited the way in which the links between lake ice phenology, local climate variables and teleconnections have been characterized and understood. In this study, our use of nonparametric methods (e.g., kernel density estimates, bootstrap) has allowed (1) improved characterization of the empirical seasonal temperature and ice out dates relationship which is inherently nonlinear, (2) better insight into how teleconnection patterns influence seasonal temperature variability, (3) better description of the link between teleconnection patterns and ice phenology in Maine lakes. For instance, it was shown in this study that NAO patterns largely influence the warm tail of seasonal winter temperature for coastal and southern climate regions while TNH patterns regulate the mean and cold tail of seasonal winter temperatures for all regions. Furthermore, the effect of teleconnection patterns on the timing of ice out dates were better characterized by determining how these patterns influence the exceedance/non-exceedance probability of the lake's winter degree-day thresholds. It should also be noted that comparison of the threshold winter degree days between nearby lakes can provide better insights into the modulating effects of lake variables (e.g., morphometry or altitude) on the link between teleconnection patterns, local climate variable and lake ice phenology.
4. It is evident from our results that pronounced negative phases of TNH influence the frequency and occurrence of early spring ice breakup in Maine lakes. While variability in TNH pattern is largely determined by the internal dynamics within the mid-latitude atmosphere, studies have shown that pronounced negative TNH phase accompany strong El Niño episodes in the Tropical Pacific (Barnston et al. 1991; Trenberth et al. 1998). El Niño is relatively well documented and well understood ocean-atmospheric phenomena and recent evidences have shown that precursor signals to El Niño events can be observed in the tropical Pacific up to 18 months in advance and their magnitude estimable 9 month ahead (Ramesh and Murtugudde 2012; Hoskins 2013). Furthermore, there are predictions in the interdecadal time scale that there will be an increase in frequency of El Niño events in a warming climate (Timmermann et al. 1999; Cai et al. 2014). It is hoped that the development of El Niño episodes over multiple seasons and its skillful forecasts (and its close association with TNH variability) can provide outlooks on seasonal to decadal patterns of early spring ice-out dates in Maine lakes.
5. So what do shifts in the ice out dates mean to the future of Maine lakes? Studies have shown that moderate to dramatic shifts in lake ice phenology induced by climate have cascading effects on the physical, chemical and biological processes in temperate lakes (Gerten and Adrian 2002; Hampton et al. 2015). For instance, during the post-1980 era, shifts towards earlier ice out dates due to winter NAO and ENSO patterns has been linked to changes in the timing, composition and magnitude of spring blooms in European and North American lakes (e.g., Adrian et al. 1999; Gerten and Adrian 2002; Park et al. 2004) although factors endogenous to the lake (e.g., nutrient availability, traits of plankton species and trophic state) may modulate the extent and intensity of change for other lakes (e.g., Adrian et al. 2006; Huber et al. 2008). Furthermore, depending on the external (e.g., light, temperature and supply of

nutrients) and internal (e.g., residence time, underwater light regime and mixing characteristics) factors, changes in the timing and duration of ice cover have also been observed to directly and/or indirectly influence timing and duration of spring turnover (Arvola et al. 2010 and references therein), water temperatures and heat budget (e.g., Arvola et al. 2010; Prowse et al. 2011), lake chemical variables (e.g., Järvinen et al. 2002; Weyhenmeyer 2009), seasonal composition and biomass of zooplankton species (e.g., Adrian et al. 1999; Gyllstrom et al. 2005), food-web interactions (e.g., Straile et al. 2003; Hampton et al. 2015), cold and warm aquatic species composition and habitat (Prowse et al. 2011) and socioeconomic values (Prowse et al. 2011) of Temperate and Arctic lakes. Our study establishes the relative role played for winter weather-climate variability on spring ice-out dates in Maine lakes and confirms the prospect of season-ahead forecasts based on climatic indices. Carefully designed lake modeling studies, that integrate weather-climate information, as well as lake-specific parameters have the potential to explicate the likelihood for transitions in lake ecosystems and functions stemming from a multitude of commingling factors (early ice out, nutrient loading, lake sediment entrainment, and increased radiative heating the lake, and mixing). In Maine, numerous lake-related activities stand to benefit from seasonal ahead forecasts, as well as identification of thresholds linked to dramatic changes in limnology induced by climate and, among other factors, urbanization.

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