

Beyene Mussie (Orcid ID: 0000-0002-1817-264X)  
Jain Shaleen (Orcid ID: 0000-0003-1792-4421)

El Niño Diversity and North American lake ice-out dates  
**Freezing Degree-day Thresholds and Lake Ice-out Dates:  
Understanding the Role of El Niño Conditions**

Mussie T. Beyene<sup>1</sup> and Shaleen Jain<sup>1</sup>

<sup>1</sup> *University of Maine, Orono, 04469, USA*

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Correspondence: **mussie.beyene@maine.edu**

ABSTRACT

In temperate lakes, the wintertime Accumulated Freezing Degree-Days (AFDD) modulate the thickness and phenology of winter ice-cover, which in turn influence lake ecosystem processes and functions across seasons. Empirical studies show that the El Niño-Southern Oscillation (ENSO)-winter AFDD relationship for North American regions depends on the location and amplitude of the winter ENSO-related sea surface temperature (SST) warming/cooling in the tropical Pacific (TP), and consequently changes in the magnitude and frequency of different ENSO patterns engender shifts and transitions in the North American lake ice regimes. For eight lakes located across North America, we found quasi-linear and nonlinear relationships between winter AFDDs and spring lake ice-out dates, and in some cases, existence of thresholds above and below which regression slopes are materially different, thus illuminating differential sensitivities. Conditional quantile functions for winter AFDDs that incorporate ENSO indices as covariates were developed to estimate the relative risk of early/late lake ice-out events for these lakes. For seven of the eight lakes, the canonical Eastern Tropical El Niño pattern increases likelihood of low winter AFDDs (associated with early ice-out dates in these lakes) by 1.5-2.8 times to that of the climatology (1951-2010 average), while the typical Central Pacific El Niño pattern corresponds to a decrease or no significant change in the occurrence probability of early ice-out dates in these Lakes. These results demonstrate that the conditional winter AFDD estimated based on a

comprehensive characterization of ENSO allow for delineation of distinct local-to-regional patterns of elevated risk of early ice out and short lake ice-cover season for North American regions.

Keywords: El Niño flavours, North American lakes, Lake ice-out dates, Quantile Regression, Conditional Risk

## 1. Introduction

In temperate and polar regions of North America, where lakes freeze during winter, wintertime accumulated freezing degree-day (AFDD)—calculated as the sum of mean daily temperature departures below the freezing point ( $0^{\circ}\text{C}$  or  $32^{\circ}\text{F}$ )—is an important cold season weather-climate variable. AFDD determines the amount of freezing energy available in the air to grow surgical ice on lakes, and consequently analytical studies often estimate the thickness of lake ice cover to be roughly proportional to the square root of the winter AFDD (Lepparanta, 2014). However, the impacts of wintertime AFDD variations on lakes may not be limited to the cold season. For example, springtime ice-out dates for Maine (USA) lakes are linked to wintertime AFDD thresholds (Beyene and Jain, 2015).

The prevailing winter climate, including the AFDD patterns over North America, has been shown to be sensitive to phases of El Niño-Southern Oscillation (ENSO), a coupled oceanic-atmospheric phenomenon in the tropical Pacific that affects weather and climate worldwide (e.g., Bonsal et al. 2001; Assel et al. 2004; Bai et al. 2012). For instance, during the 1997/98 El Niño event (warm phase of ENSO), northern US and southern

Canada recorded one of their lowest winter AFDDs such that it resulted in the least extensive ice-cover in the Great Lakes over the past century. However, the severity and spatial extent of the North American weather and climate anomaly patterns associated with El Niño events is neither alike nor is it linearly opposite to that of La Niña (cold phase of ENSO) events (e.g., Wyrski, 1975; Hoerling and Kumar, 1997; Hoerling et al. 1997). Studies have shown that such discrepancies may arise from differences in the location and amplitude of their signature SST anomalies in the tropical Pacific as variations in the location of the warmest waters ( $SST > 27.5^{\circ}C$ ) in the tropical Pacific generate differential atmospheric wave trains responsible for climate variability worldwide (e.g., Barsugli and Sardeshmukh, 2002; Hoerling and Kumar, 1997). Furthermore, Beyene and Jain (2017) showed that the sensitivity of North American winter temperatures to diverse ENSO flavours is not uniform, both regionally and across different parts of the empirical probability density function (EPDF). In the present context, a salient question is: to what extent do distinct El Niño flavours affect North American lake ice-out dates through their differential effect on the (EPDF of) winter AFDD? Two aspects of current and future ENSO variability further motivate the above noted line of inquiry: (a) five-fold increase in the frequency of a “new variant” of ENSO is being projected under anthropogenic climate change (e.g. Yeh et al. 2009; Cai et al. 2014), (b) ENSO-based climate forecasts on seasonal and longer lead-times have proven to be reliable (Hoskins, 2013). To this end, this study aims to develop location specific risk functions for North American winter AFDD,

that incorporate as covariates ENSO indices that capture the location and amplitude of tropical Pacific SST anomalies, in order to estimate ENSO-related changes in the relative occurrence probability of early/late lake ice out events in North America. In this study, the term occurrence probability is used interchangeably with risk and likelihood.

Past lake ice studies often assessed ENSO-induced changes in lake ice season by characterizing the response of local meteorological variables (relevant to lake ice evolution) to large-scale climate patterns using traditional statistical methods such as linear regression and averaging of sub-samples. However, analyses employing these methods offer limited insight, as they primarily measure the shift in the conditional mean and not the conditional tails of the distribution, where climate-related thresholds in lakes usually reside. This study thus employs quantile functions, first proposed by Koenker and Bassett (1978), to investigate the response of North American winter AFDD, across its variability range, to the amplitude and location of tropical Pacific SST warming/cooling, linked to ENSO events. This approach provides a functional framework to estimate the winter AFDD conditioned on ENSO indices with three important features: (a) no distributional assumption, (b) quantification of differential sensitivity across quantiles, and (c) resistance to outlier effects.

Beyene and Jain (2017) have shown that the change in the conditional risk of North American winter temperatures due to ENSO flavors varies both regionally and across different temperature quantiles. This study extends their work and aims to quantify ENSO

related changes in North American lake ice out dates by characterizing its effect on winter AFDD variability. Two key tasks in this regard are as follows:

- (1) Quantify the nature of relationships between lake ice and winter AFDD variability, based on observational records for a select group of lakes across North America.
- (2) Estimate ENSO-related changes in the relative likelihood of early/late lake ice out events for eight North American lakes—location-specific risk functions for North American winter AFDD that incorporate ENSO indices as covariates are developed.

## 2. Data and Methods

*Lake Ice-out (off) Dates:* Lake ice-out date refers to the date when winter ice completely disappears from the lake surface. In this study, eight North American lakes (see Figure 1 for lake locations) that freeze during the winter were selected and their historical lake ice-out dates from 1950-2010 were downloaded from the following electronic databases:

Global Lake and River Ice Phenology Database (at National Snow and Ice Data Center) and Lake Ice Clearance and Formation dataset (at Niwot Ridge Long Term Ecological Research Center). In Supplementary Table 1, geomorphological data and site of observation for ice out dates is provided for the eight selected lakes.

*North American Winter AFDD:* Time series of gridded, daily mean temperature data for North America from 1951-2010 were derived from HadGHCND dataset (Caesar et al.

2006), which provides station-based, daily observations of average temperature data on a  $2.5^\circ \times 3.75^\circ$  grid resolution. The year-to-year winter AFDD for North American fields were then calculated as the daily degrees below freezing ( $0^\circ\text{C}$ ) summed over the total number of days from December to February that the daily average temperature was below freezing:

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

where  $\Delta t$  is the time interval ( $\Delta t = 1$  day),  $n$  is the number of days from December to February months ( $n = 90$  or  $91$ ),  $T_i$  is the daily mean temperature ( $^\circ\text{C}$ ) and  $T_0$  is the freezing temperature for water ( $T_0 = 0^\circ\text{C}$  or  $32^\circ\text{F}$ ). Lake ice occurs predominantly in regions with regular occurrence of sub-freezing temperatures and wintertime AFDD. Climatological winter AFDD patterns over North America (Figure 1a, b) indicate that regions with pole ward of  $35^\circ\text{N}$  show appreciable below-freezing temperatures; this region will be the focus of investigation in the remainder of this study.

*Relationship between AFDD and lake ice thickness:* Lake ice formation and growth results from the dynamical heat balance at lake surface. (Lepparanta 2014). Given that the surface air temperature strongly relates to major energy fluxes from lake to atmosphere, analytical studies often use the degree-day method— first derived by Stefan (1891) — to approximate the thickness of winter ice formed on lake surface. In general, in a degree-day model, ice growth ( $h$ ) in inches, is modelled as a function of the square root of the accumulated

freezing degree-days (*AFDD*)

$$h = C\sqrt{AFDD} \quad (2)$$

where  $C$  is a coefficient that accounts for local snow and atmospheric conditions and  $AFDD$  is in Degree-Day Fahrenheit (DDF) (e.g., Assur 1956). In Supplementary Analysis 2 section, we provide a detailed exposition of this physical basis of the relationship noted above.

*ENSO Indices:* The emergence, type and strength of El Niño /La Niña events are often based on areal averaged SST indices for four regions in the tropical Pacific: Niño 1+2, Niño 3, Niño 3.4 and Niño 4 (see supplementary Figure S1a). In this study, time series of monthly, spatially averaged SSTs for the four Niño regions from 1951-2010 were collected from a dataset prepared by NOAA's Climate Prediction Center, based on extended, reconstructed sea surface temperature (ERSST) V4 dataset. Time series of winter Niño SST indices from 1951-2010 were then computed by averaging the December to February SST index for each Niño region (see Supplementary Figure S1b).

Geographical distributions of ENSO-related tropical Pacific SST anomalies (warming or cooling relative to long-term averages) have been identified as important contributors to the spatial patterns and severity of climatic impacts in remote regions. Thus, it is critical to identify a small set of ENSO indices that best represent the detailed pattern of SST warming or cooling in the tropical Pacific. In this study, Principal Component



Analysis was performed on the time series of mean winter SST indices of the four Niño regions from 1951-2010 (see Supplementary Analysis 1). The resulting pair of indices (Principal Component 1 and 2, hereafter referred as PC1 and PC2) account for 99.8% of the total variance in the ENSO historical record (PC1 = 89% and PC2 =10.8%). While PC1 and PC2 time series comprehensively characterize the temporal variations in ENSO over the past six decades, the spatial loadings linked to these PCs offer helpful interpretation of the tropical Pacific warming and cooling patterns associated with ENSO events (see Supplementary Figure S2). PC1 loadings across the four Niño regions are of the same sign suggesting synchronous wintertime SST variation across all Niño regions (see Supplementary Table 2b and Supplementary Figure S2b). PC2 loadings are characterized by an east-west dipole pattern with the wintertime SSTs in Niño-1+2 (eastern Pacific) region varying out of phase with that of Niño-3.4 and Niño-4 (Central Pacific) regions (Supplementary Figure S2c). Beyene and Jain (2017) and others have showed that the joint indices of PC1 and PC2 allow characterization of the amplitude and location of maximum TP SST anomalies associated with diverse El Niño/La Niña events (see Supplementary Analysis 1). Therefore, PC1 and PC2 indices are used as covariates/predictors in the quantile regression pursued in this study. Finally, as noted in the previous section, recent improvements in the understanding on ENSO flavors imply distinct patterns of climatic impacts across North America, and projected trends for the 21<sup>st</sup> century reveal dramatic

shifts in ENSO frequency—the associated risk to environmental variables such as lake ice remains unclear.

*Quantile Regression:* Historical winter AFDD variability at a particular location can be summarized based on a frequency distribution or probability density function (PDF). Characteristic AFDD values that correspond to specific quantiles (representing non-exceedance probability) can be obtained from the PDF. For instance, the AFDD value for the 0.25<sup>th</sup> quantile is exceeded 75% of the time. An extension of this approach allows modelling of quantiles based on covariates or predictors (for example, ENSO conditions) that modulate the conditional quantile functions for the target variable (in our case, AFDD). In its general form, quantile regression (Koenker and Hallock 2001) affords conditional quantile estimates for each quantile, and as such, conditional PDF. These estimates are superior to ones from linear regression, wherein covariate effects are restricted to affect on the mean of the target variables. Example applications of quantile regression in lake studies include Bissinger et al. (2008), Fielding (2013), and Xu et al. (2015).

In this study, the quantile regression approach is used to model and predict the linear response of North American winter AFDDs, across all or selected quantiles, to ENSO indices ( $X_i$ ). Mathematically, this can be expressed as

$$AFDD^{(\tau)} = \beta_0^{(\tau)} + \beta_1^{(\tau)}PC1 + \beta_2^{(\tau)}PC2 \quad (3)$$

where  $\beta_0^{(\tau)}$  is the intercept, and  $\beta_1^{(\tau)}$  and  $\beta_2^{(\tau)}$  are the slope coefficients for PC1 and PC2 patterns at  $\tau^{\text{th}}$  quantile. The regression parameters  $\beta^{(\tau)}$  are obtained by solving for minimization of the sum of weighted absolute residuals. The quantile regression implementation in the R computing environment (Koenker, 2017) is employed to provide the optimizing algorithm to estimate  $\beta^{(\tau)}$  using linear programming techniques. Estimation of conditional winter AFDD quantiles requires fitting of curves across each quantile independently and as such generating multiple conditional winter AFDD quantile functions may yield quantile curves that cross or overlap, creating an invalid distribution. To alleviate the crossing problem in quantile regression, a procedure introduced by Bondell et al. (2010), which imposes a non-crossing constraint, is applied. The statistical significance for parameter estimates,  $\beta^{(\tau)}$  in the conditional winter AFDD functions were assessed by constructing the confidence interval using the wild bootstrap method, an approach that is almost unaffected by residual heterogeneity (Feng et al. 2011).

### 3. Results

#### *3.1 Winter AFDD and North American Spring Lake Ice-out Dates*

Empirical and theoretical rationales are needed to establish the import of seasonal winter (December-February) AFDD on North American lake ice season. To this end,

Supplementary Analysis 2 presents a synopsis of the theoretical-physical basis underlying AFDD-lake ice linkages. This section on the other hand, offers empirical findings by analyzing the observed response of spring lake ice-out dates to their antecedent winter AFDDs for eight North American lakes (see Figure 1a). Here, the efficacy of winter AFDD in conditioning the spring lake ice out dates was examined using non-parametric kernel regression approach, as the functional relationship between winter AFDD and spring ice-out dates is unknown and may vary across lakes. Kernel regression method (Silverman 1986) is based on a smoothing approach that is locally adaptive, thus allowing for the estimation of linear and nonlinear relationship from data. The degree of smoothing depends on the bandwidth, which is selected based on a minimization of integrated error (Bowman and Azzalini, 1999). In the context of ice-out and winter AFDD relationship, of particular interest is the diagnosis of nonlinearity and potential break points in the relationship (akin to thresholds).

Results of this analysis show that for all selected lakes, there is a positive (direct) relationship between winter AFDD and spring ice-out dates, which implies that winters with relatively low (high) winter AFDDs are generally related to earlier (later) than normal lake ice-out dates the following spring (see Figure 1c-j). However the degree of sensitivity of spring ice-out dates to winter AFDDs in these lakes varies both spatially and across different winter AFDD quantiles. For instance, contrasting the overall slope of the winter AFDD regression line across the eight lakes indicate that the response of spring ice-out

dates to the antecedent winter AFDD variability is relatively stronger at Lake Superior (USA) and Damariscotta Lake (USA) as compared to those at Lake Albion (USA) and Long Lake (Canada). This implies that the strength of association between spring ice-out dates and the antecedent winter AFDDs for North American lakes shows geographical variation and locally, is also likely to be modulated by other factors such as morphometry, elevation, and continentality. On the other hand, examining the response of spring ice-out dates of the eight lakes across different winter AFDD quantities reveals that unusually low /high winter AFDDs are strongly related to early/late spring ice-out dates. For instance, for Damariscotta Lake, 5 of the 6 winters with AFDD less than 200 Degree Day Celsius (DDC) ( $\tau d 0.30^{\text{th}}$ ) are associated with ice-out dates earlier than April 3<sup>rd</sup> (see figure 1H). Similarly for Lesser Slave Lake (Canada), 5 of the 6 winters with AFDD less than 2270 DDC ( $\tau d 0.28^{\text{th}}$ ) are linked to ice out dates that occurred prior to May 15<sup>th</sup> (see figure 1D).

These findings on the presence of winter AFDD quantities that correspond to early/late spring ice-out dates for North American lakes is consistent with the findings reported in Beyene and Jain (2015). This implies that the efficacy of ENSO events in modulating the variability of ice-out dates in lakes depends on their effect on the occurrence of winter AFDDs associated with ice-out dates. Thus, characterization of ENSO-related change in risk of early/late ice dates requires an understanding of the relationship between different El Nino (or La Nina) events and winter AFDD at specific quantiles, as well across the entire winter AFDD distribution. It should be noted that for

studied lakes, the degree of coherence between winter AFDD and spring ice-out dates can generally be assumed to be independent of spring temperature conditions, as there is no significant ( $p < 0.1$ ) correlation between winter and spring AFDD for almost all North American regions (see Supplementary Figure S4).

### ***3.2 ENSO Diversity and North American Winter AFDD Variability***

Differences in the location of peak ENSO-related Sea Surface Temperature (SST) warming/cooling in the Tropical Pacific (TP) contribute to the observed variability in ENSO-related climate patterns in North America (e.g., Hoerling and Kumar, 1997). To illustrate this difference in the context of North American winter AFDD, five years were selected where by majority agreement of different ENSO identification methods (EP/CP method, Niño3/4 method, EMI method and regression-EOF method) have been determined as Central Pacific (CP) El Niño (1969, 1988, 1995, 2003, 2005, 2010), Eastern Pacific (EP) El Niño (1973, 1983, 1987, 1998, 2007) and La Niña events (1956, 1971, 1974, 1976, 1989) (see Supplementary table 1). It should be noted that our use of EP and CP El Niño terminology in this study serves only to contrast the site of peak SST warming in TP between the two El Niño patterns, and is by no means implying that these patterns are distinct modes of El Niño. The composite TP winter SST anomaly (departure from the long-term average) pattern for the five CP El Niño events selected features peak SST warming confined in the central TP regions (Niño3.4 and Niño4 regions) flanked by cooler

than normal SSTs on both sides of the equatorial Pacific (see Figure 2a bottom). While there is some inter-event differences, the pattern of North American winter AFDD variability pattern corresponding to CP El Niño events can broadly be characterized as southeast-northwest dipole pattern, where there is relatively strong increase in the seasonal winter AFDD (colder temperatures) over the Midwest and northeast US regions and decrease in winter AFDD (warmer temperatures) over western US and Canadian regions and northern edges of Canada (see Figure 2a top). In contrast, the location of maximum SST warming in the TP during EP El Niño winters is concentrated in eastern TP extending from the western coast of South America to the regions east of the dateline (Niño1+2 & Niño 3 regions) (see Figure 2b). Moreover, these events are associated with a significant decrease of winter AFDD over much of North America (except for the Pacific US regions and Baffin Island). These results illustrate that the location of maximum SST warming in the tropical Pacific has important implication on the impact of individual El Niño events on the winter AFDD over US and Canada. On the other hand, the composite TP winter SST anomaly pattern for the five La Niña events exhibits peak SST cooling over central-eastern equatorial Pacific (Niño3 and Niño4 regions). Moreover, the North American winter AFDD anomaly patterns related to these events generally features a northwest-southeast dipole pattern with a relatively strong increase in winter AFDD over western Canada and Alaska and decrease in winter AFDD over the Southeast US states. These results reveal the effect of La Niña events on the winter AFDD of various North American regions is not a mirror

opposite to that of El Niño events. They also establish the significance of tropical Pacific in producing non-linearity in the response of North American winter AFDD to opposite phases of ENSO.

In summary, the above findings show that the ENSO-winter AFDD relationship for North America varies with the location of peak ENSO-related SST warming and/or cooling in the TP. In other words, the efficacy of El Niño (or La Niña) events in modulating the conditional winter AFDD distribution for North American regions shows spatial variation. Consequently, in the face of EP or CP El Niño/La Niña episodes, the likelihood associated with various AFDD magnitudes, including the ones that correspond to early/late spring ice-out dates in North American lakes, is marked by differential sensitivities. Quantile regression framework offers conditional risk estimates of AFDD at a location as well as regional scale.

### ***3.3 ENSO Patterns and Lake Ice Season Risk Assessments***

It was noted in earlier sections that there are winter AFDD quantities that correspond to early/late spring ice-out dates for North American lakes. The efficacy of quantile functions in generating AFDD quantiles conditioned on ENSO indices can thus offer usable risk estimates for unusually early/late ice-out events in these lakes. For instance, figure 3a shows that for Lake Superior, winters with AFDDs less than 820 Degree-day Celsius (DDC) ( $\tau < 0.31^{\text{th}}$ ) are strongly associated with spring lake ice-out dates prior to March



30<sup>th</sup>, and according to the climatology, the occurrence probability of such “mild winters” is 0.30. Please note that the method used here for determining the winter AFDD threshold is highly subjective and as such serves only for illustrative purposes only. To estimate the change in the conditional risk of early lake ice-out dates at Lake Superior due to ENSO patterns, a set of quantile functions for winter AFDD (that incorporate ENSO indices as covariates) were fitted at  $\tau = 0.01$  intervals over the quantile range ( $0.01 < \tau < 0.99$ ) and these function were used to compute winter AFDDs at the respective quantiles for sample combination of PC1-PC2 indices. Figure 3b shows the resulting conditional winter AFDD distribution as well as conditional risk of winter AFDDs less than 820 DDC for archetypical ENSO flavors (derived as centroids of PC1-PC2 index for the five selected EP, CP El Niño and La Niña events mentioned in the first result section). From these, it can be observed that during archetypical EP El Niño events, the likelihood of mild winters that engender early ice-out dates at Lake Superior increases by 2.16 times relative to that of the climatology (probability = 0.31). During typical CP El Niño pattern however, there is no significant change in the occurrence probability of early ice out dates at Lake Superior relative to that of the climatology. Contrary to the traditional assumption, this result highlights that the effect of different El Niño flavors on North American lake ice-out dates are not alike. Figure 3c extend the results in figure 3b to depict the change in risk (relative to that of the climatology) of early ice-out dates for sample combinations of PC1 and PC2 indices. Broadly speaking, the conditional risk of early ice-out dates at Lake Superior

increases from region of negative PC1 and positive PC2 to a region of positive PC1 and negative PC2. This means that strong EP El Niño patterns ( $PC1 > 2$  &  $PC2 < 0$ ) are related to an increase the relative likelihood of early ice-out dates at Lake Superior by 1.2 - 2.5 times that of the climatology, while strong CP El Niño events ( $PC1 > 1$  &  $PC2 > 0$ ) correspond to a rise in the relative risk of early ice out dates by 0.9-2.4 times. On the other hand, La Niña events ( $PC1 < -1.5$  &  $PC2 < 0$ ) reduce the relative occurrence probability of mild winters by 0.6-1.

Diversity in the influence of different ENSO patterns on North American lake ice-out dates can be illustrated by contrasting the change in the likelihood of mild winters that produce early ice-out dates, due to the three archetypical ENSO patterns, for the eight North American lakes. Results reveal that the effect of ENSO pattern on the timing of North American spring lake ice-out dates varies both spatially and for different ENSO events (see Figure 4). For seven of the eight lakes, the archetypical EP El Niño pattern increases the likelihood of mild winters that correspond to early ice-out dates, by 1.5-2.8 times to that of the climatology, while for Deadman's Pond the occurrence probability of such winters decreases by 0.63 times relative to the climatology. In contrast, at Damariscotta Lake and Deadman's Pond, typical CP El Niño pattern decreases the likelihood of mild winters that are associated with early ice out dates, by 0.4-0.8 times to that of the climatology, while for the other six lakes it has modest or no effect on the risk of such winters. On the other hand, for Lake Albion (Deadman's Pond), archetypical La Niña pattern reduces (increases) the

occurrence probability of mild winters by 0.46 (1.2) times to that of the climatology, while for the other six lakes, it is associated with modest or no changes in risk of early ice out dates. These results taken together show that for North American lakes, (a) the effect of EP El Niño on the timing of ice-out dates is quite distinct to that of CP El Niño from local-to-regional scale, (b) El Niño related changes in the timing of spring ice-out dates is not a linear opposite to that of La Niña events. As discussed in earlier sections, these effects stem from the asymmetry in the regional AFDD patterns associated with El Niño/La Niña flavors and distinctness of AFDD thresholds for ice-out dates among local lakes. Supplementary figure S6-S10 depicts the wintertime AFDD quantities that correspond to early ice out date in lakes and the results of the conditional risk analysis for sample combinations of PC1 and PC2 for the seven other lakes.

#### **4. Discussion and Summary**

ENSO-related warming/cooling in the tropical Pacific sea surface temperatures cause systematic shifts in the North American wintertime Accumulated Freezing Degree-days (AFDD) patterns. Winter AFDD governs the thermal flux between lake and atmosphere to grow lake ice, and early/late spring ice-out dates have been sensitively linked to seasonal winter AFDD thresholds. Consequently, changes in the magnitude and frequency ENSO has the potential to cause shifts and transitions in the ice regime of North American lakes. Our analysis of the response of spring ice-out dates to winter AFDD for select North

American lakes reveals two important features. One is that for North American lakes, the relationship between winter AFDD and spring lake ice-out dates can be characterized from quasi-linear to highly non-linear. Second, in a number of these relationships, there are AFDDs (thresholds) that are strongly associated with specific ice out dates. Thus, the conditional quantile regression approach developed in this study allows a detailed characterization of quantile-specific ENSO-AFDD that can be readily used to estimate risk functions for AFDD and lake ice out conditioned on ENSO. Results for seven out of the eight North American lakes show that typical Eastern Pacific (EP) El Niño pattern is associated with an increase in the risk of low winter AFDDs (that produce early ice-out dates in these lakes) by 1.5-2.8 times to that of the climatology, while the typical Central Pacific (CP) El Niño pattern corresponds to a decrease or no significant change in the likelihood of early ice-out dates in these lakes. On the other hand, for Deadman's Pond (Lake Albion) the archetypical La Niña pattern induces an increase (decrease) the occurrence probability of early ice out dates by 1.2 (0.46) times relative to that of the climatology. To summarize: (a) the effect of CP and EP El Niño on the timing of spring ice-out dates of North American lakes is distinct from local-to-regional scale, (b) for North American lakes, the change in the timing of spring ice-out dates due to El Niño and La Niña patterns is not linearly opposite. In conclusion, we offer the following observations and discuss emerging research directions:

1. This work broadens current understanding of ENSO-related AFDD teleconnections for North America. In doing so, the relative contributions of ENSO flavors (delineated as the two leading pattern of tropical Pacific SSTs) in modulating AFDD distribution as a whole, and select AFDD thresholds (associated with lake ice-out dates) for North American regions was quantified.. Detection and evolution of ENSO events in the tropical Pacific is a well understood subject and as such, magnitudes of ENSO events are estimable up to 9 months in advance (e.g. Ramesh and Murtugudde, 2012; Hoskins, 2013). These imply that the ENSO-related conditional risk functions developed here pave the way for use of seasonal and longer-lead ENSO forecasts that can be profitably used to anticipate shifts in lake ice out dates.
2. The quantile regression risk framework advanced in this study, while specific to lake ice out, is applicable to other lake variables to assess climate-related risk and vulnerability. While a linear approach was taken here, nonlinear and non-parametric approach can be used to model complex relationships (for example, ones involving lake chemistry).
3. Changing weather/climate patterns reflect trends and inter-annual variability (for example, due to ENSO). Resulting seasonal temperatures can disrupt the lake phenology and linked processes, species dynamics and succession, and nutrient loading and mixing characteristics. For instance, for temperate and arctic North

American lakes, winter climate variability has directly or indirectly been shown to affect ice cover phenology and extent (e.g. Bai et al. 2012; Beyene and Jain 2015), water temperatures (e.g. Austin and Colman 2007), onset of stratification period (e.g. Winder and Schindler 2004), seasonal plankton composition, abundance and succession (e.g. Goldman et al. 1989; Hampton et al. 2017), fish population (e.g. Farmer et al. 2015) and seasonal geo-chemical dynamics (e.g. Joung et al. 2017; Powers et al. 2017). In a changing climate, successful conservation and restoration of lake ecosystems can benefit from climate-based risk framework presented here, thus affording pinpointed estimates of trends and transitions in lake variables. Finally, improved understanding and prediction of lake and river ice conditions has important environmental and socio-economic (e.g. recreational, hydro-power generation, cultural, commercial) implications, a point underscored in recent studies (e.g., Prowse et al. 2011; Durnford et al., 2017).

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## List of Manuscript Body Tables

Table 1: Ratio of conditional likelihood of selected winter AFDDs over lakes due to ENSO events, to that of the unconditional. Results are computed using the same techniques as in figure 3b.

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Table 1: Ratio of conditional likelihood of selected winter AFDDs over lakes due to ENSO events, to that of the unconditional. Results are computed using the same techniques as in figure 3b.

Lake	Ice out dates corresponding to winter AFDD		Unconditional probability of W* for the 1951-2010 period	Conditional risk relative to the Unconditional probability		
	Winter threshold (W*) in DDC units	Ice-out Date corresponding to W*		Eastern Pacific El Niño	Central Pacific El Niño	La Niña
Damariscotta	200	3-April	0.14	1.57	0.78	0.93
Superior <sup>#</sup>	820	31-March	0.31	2.16	1.06	0.83
Winnipeg	2015	13-May	0.26	3.3	0.43	1.06
Lesser Slave	2170	13-May	0.28	1.67	0.93	0.82
Dease	2170	28-May	0.1	1.7	1.2	0.5
Deadman's Pond	1735	3-May	0.3	0.63	0.7	1.2
Long	2730	26-May	0.2	2.5	0.85	0.7

AFDD- Accumulated Freezing Degree days

DDC- Degree-day Celsius

## List of Manuscript Body Figures

Figure 1: Climatology of winter Accumulated Freezing Degree Days (AFDD) over North America and its relationship with lake ice-out dates. North American map of the (a) mean, (b) standard deviation of winter AFDDs from 1951-2010. Contour intervals for the mean and standard deviation winter AFDD are set at 300 and 40 Degree-day Celsius (DDC) respectively. The red coloured polygons represent the location of the eight selected lakes. Plotting lake ice-out dates as a function of winter AFDD at (c) Dease Lake (d) Lesser Slave Lake (e) Lake Winnipeg (f) Lake Albion (g) Deadman's Pond (h) Damariscotta Lake (i) Lake Superior (j) Long Lake. The filled/unfilled polygons in each scatter plot represent the ice out date as a function of winter AFDD for each lake. The red line denotes locally averaged lake ice out date conditioned on the winter AFDD, and is computed using non-parametric kernel regression method. The blue shadings designate the 90% confidence band for a linear model.

Figure 2: Composite maps of tropical Pacific winter SST warming/cooling and associated North American winter Accumulated Freezing Degree-days (AFDD) anomalies for select five (a) Central Pacific (CP) El Niño (b) Eastern Pacific (EP) El Niño (c) La Niña events. These events were chosen by majority consensus across different identification methods in the literatures (see Supplementary Table 3). Anomalies are computed as departure from the 1951-2010 average and contour intervals for winter AFDD and SST anomalies are 40 Degree day Celsius (DDC) and  $0.25^{\circ}$  Celsius respectively. Stippled areas denote regions where the departure is significant at 90% confidence level based on two-tailed re-sampling tests.

Figure 3: Risk estimates for winter Accumulated Freezing Degree-day (AFDD) quantities, corresponding to spring ice-out dates earlier than April 1<sup>st</sup> at Lake Superior, conditioned on different El Niño /Southern Oscillation patterns. (a) Scatter plot for spring ice-out dates at Lake Superior as a function of the antecedent winter AFDD. The grey unfilled circles denote the winter AFDD associated with observed ice out dates. The purple line represents locally averaged lake ice-out dates conditioned on the winter AFDD, and is computed using non-parametric kernel regression method. The blue shadings denote the 90% confidence band for computed regression line. (b) Conditional winter AFDD distribution at Lake Superior associated with the three archetypical ENSO patterns: CP El Niño (blue), La Niña (green) and EP El Niño (red). The grey area represents part of the conditional distribution less or equal to 820 Degree-day Celsius (DDC),. The conditional winter AFDD distribution curves for typical ENSO patterns was constructed by generating conditional quantile functions for estimating winter AFDD at  $\tau = 0.01$  intervals over the quantile range ( $0.01 < \tau < 0.99$ ), followed by estimation of winter AFDD quantiles at the centroid of five selected samples of ENSO flavours in the PC1-PC2 phase space. (c) Contour surface plot of estimated conditional risk for winter AFDD at Lake Superior to be less or equal to 820 DDC, relative to the unconditional (climatology). The dark filled circles represent the PC1-

PC2 indices for the three archetypical ENSO patterns, while the grey polygon represents the convex hull – region containing observed PC1-PC2 values. The colour key for ratio of risk conditioned on PC1-PC2 values is given at the bottom.

Figure 4: Risk estimates for winter Accumulated Freezing Degree-days (AFDD) quantities (thresholds), corresponding to early ice-out dates for selected North American lakes, conditioned on three archetypical ENSO patterns. At each lake, the blue, green and red curves denote the conditional winter AFDD distribution associated with Central Pacific (CP) El Niño, La Niña and Eastern Pacific (EP) El Niño respectively, while the black curve represents the unconditional winter AFDD distribution for the 1951-2010 period. The steps by which the conditional distributions are generated are given in the caption for figure 3b. The grey area signifies part of the conditional distribution less or equal to specific AFDD threshold (broken black line). The confidence intervals for risk estimates was determined by computing the occurrence probability of each year conditioned on its PC1-PC2 index and determining the 5<sup>th</sup> and 95<sup>th</sup> percentile from the time series of risk estimates. Conditional non-exceedance probability (risk) estimates in bold are significant at 10% significance level.



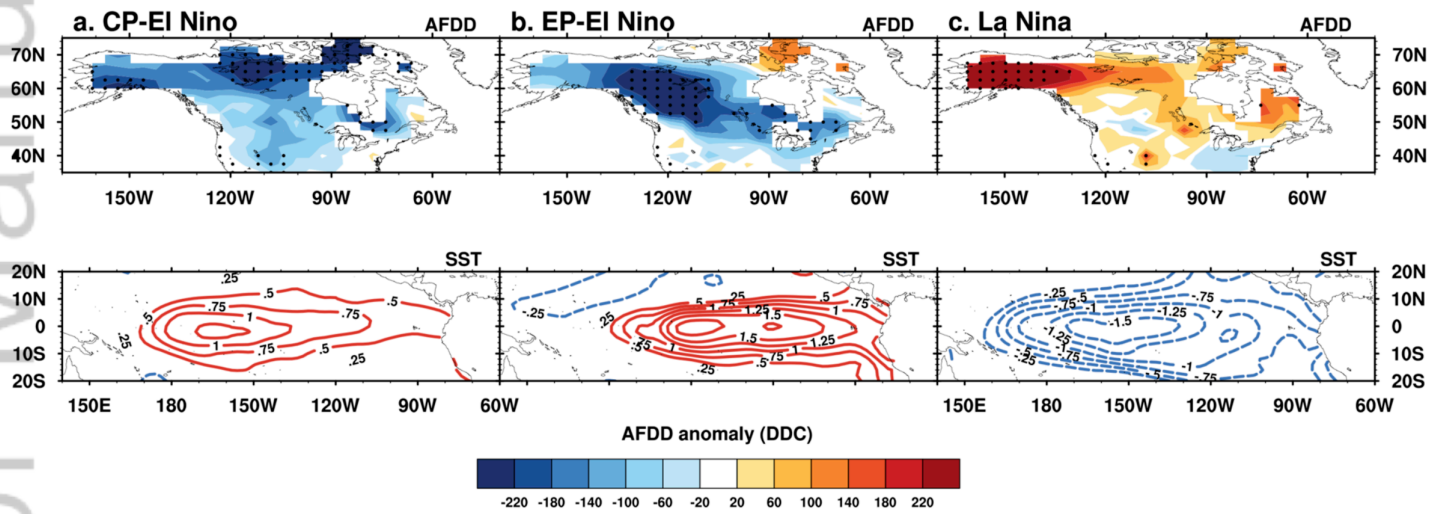


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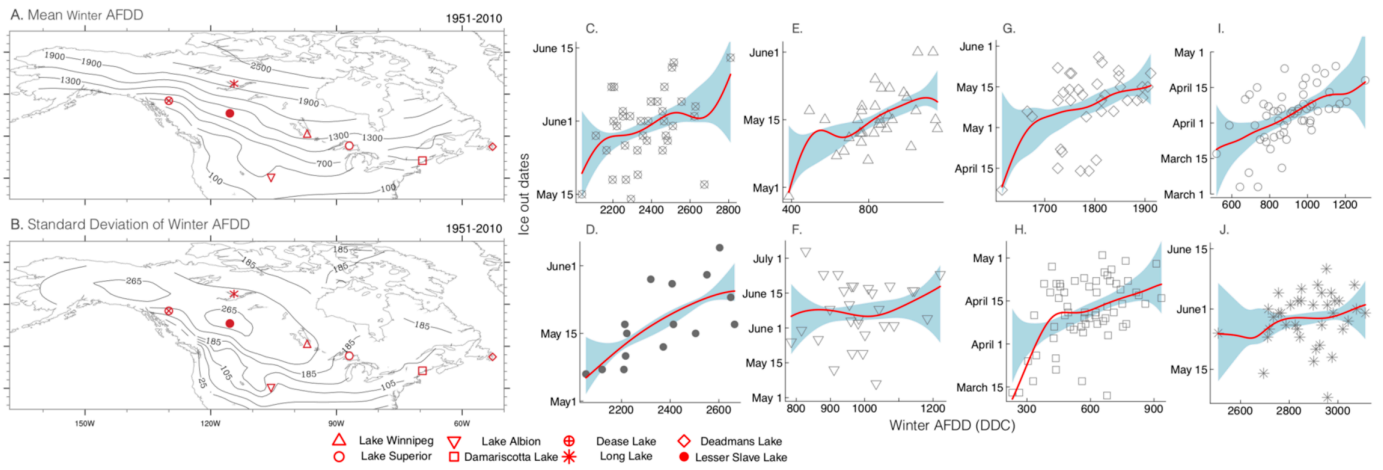


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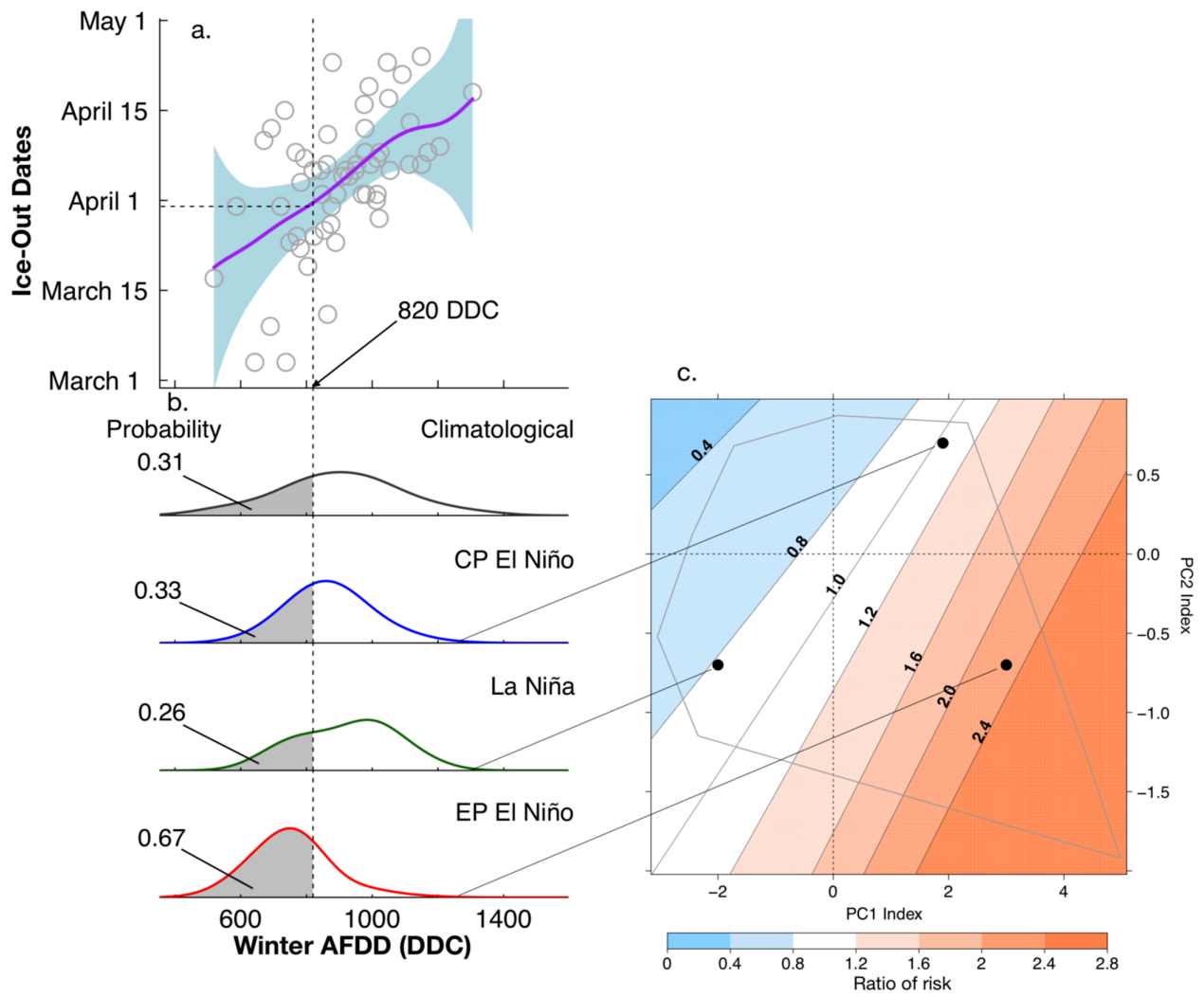
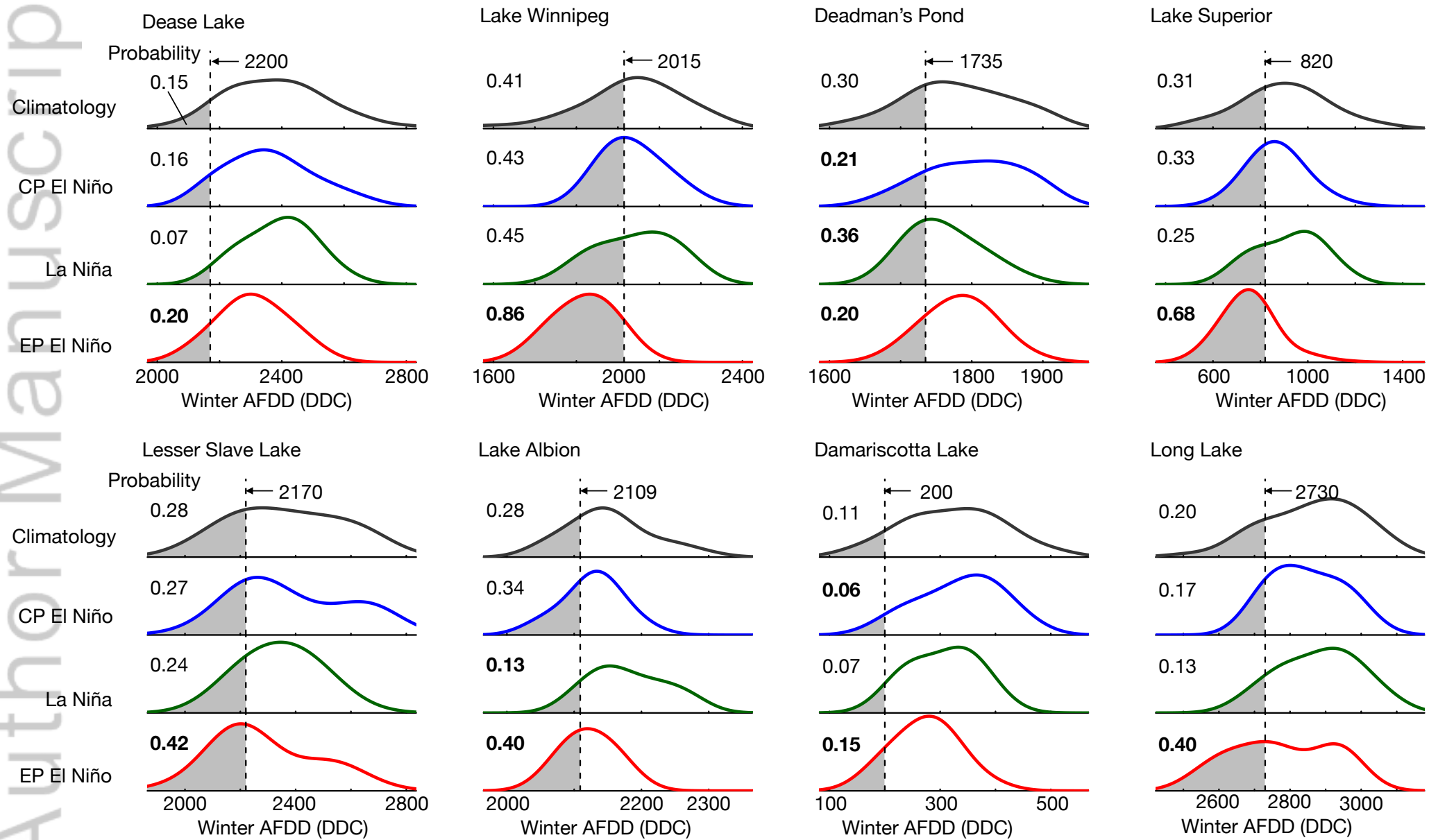


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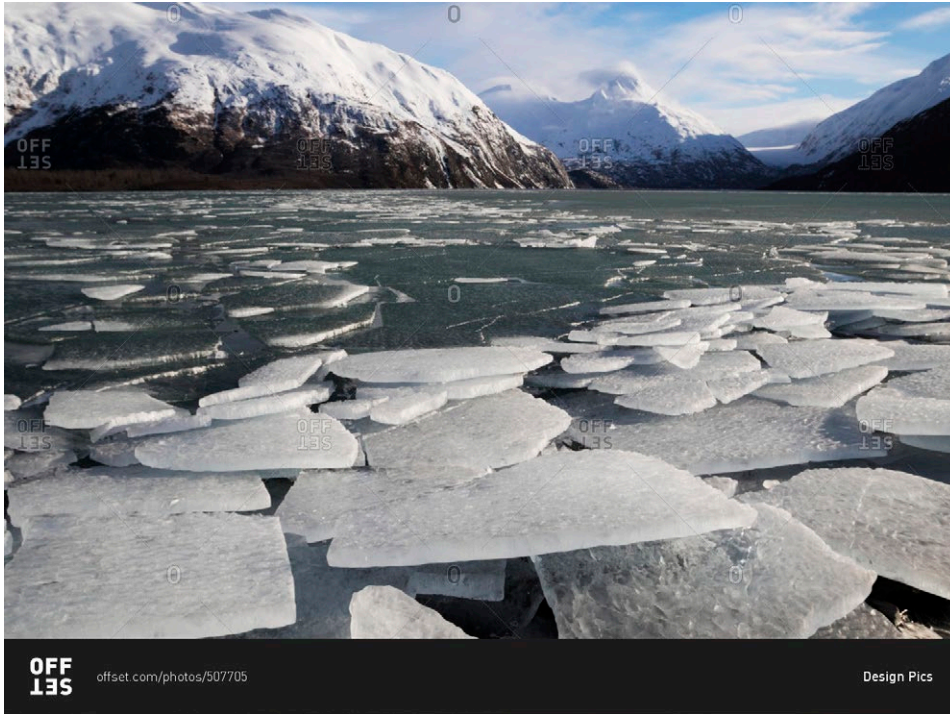
Figure 4

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# Freezing Degree-day Thresholds and Lake Ice-out Dates: Understanding the Role of El Niño Conditions

Mussie T. Beyene\* and Shaleen Jain



The timing of spring ice-out dates of lakes is sensitive to the prevailing winter Accumulated Freezing Degree Days (AFDD). Empirical studies show that the El Niño-Southern Oscillation (ENSO)-winter AFDD relationship for North American regions depends on the spatial patterns of ENSO-related sea surface temperature (SST) warming/cooling in the tropical Pacific (TP). Using conditional quantile functions for winter AFDDs that incorporate ENSO indices as covariates, we show that for North American lakes, (a) the effect of EP El Niño on the timing of ice-out dates is quite distinct to that of CP El Niño from local-to-regional scale, (b) El Niño related changes in the timing of spring ice-out dates is not a linear opposite to that of La Niña events.

1                   **Freezing Degree-day Thresholds and Lake Ice-out Dates:**  
2                   **Understanding the Role of El Niño Conditions**

3  
4                   Mussie T. Beyene<sup>1</sup> and Shaleen Jain<sup>1</sup>

5                   <sup>1</sup> *University of Maine, Orono, 04469, USA*

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21 Correspondence: **[mussie.beyene@maine.edu](mailto:mussie.beyene@maine.edu)**

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ABSTRACT

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In temperate lakes, the wintertime Accumulated Freezing Degree-Days (AFDD) modulate the thickness and phenology of winter ice-cover, which in turn influence lake ecosystem processes and functions across seasons.

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Empirical studies show that the El Niño-Southern Oscillation (ENSO)-winter AFDD relationship for North American regions depends on the location and amplitude of the winter ENSO-related sea surface temperature (SST)

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warming/cooling in the tropical Pacific (TP), and consequently changes in the magnitude and frequency of different ENSO patterns engender shifts and

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transitions in the North American lake ice regimes. For eight lakes located across North America, we found quasi-linear and nonlinear relationships

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between winter AFDDs and spring lake ice-out dates, and in some cases, existence of thresholds above and below which regression slopes are

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materially different, thus illuminating differential sensitivities. Conditional quantile functions for winter AFDDs that incorporate ENSO indices as

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covariates were developed to estimate the relative risk of early/late lake ice-out events for these lakes. For seven of the eight lakes, the canonical Eastern

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Tropical El Niño pattern increases likelihood of low winter AFDDs (associated with early ice-out dates in these lakes) by 1.5-2.8 times to that of

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the climatology (1951-2010 average), while the typical Central Pacific El Niño pattern corresponds to a decrease or no significant change in the

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occurrence probability of early ice-out dates in these Lakes. These results demonstrate that the conditional winter AFDD estimated based on a

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comprehensive characterization of ENSO allow for delineation of distinct local-to-regional patterns of elevated risk of early ice out and short lake ice-

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cover season for North American regions.

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Keywords: El Niño flavours, North American lakes, Lake ice-out dates,

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Quantile Regression, Conditional Risk

## 50 **1. Introduction**

51 In temperate and polar regions of North America, where lakes freeze during winter,  
52 wintertime accumulated freezing degree-day (AFDD)—calculated as the sum of mean daily  
53 temperature departures below the freezing point ( $0^{\circ}\text{C}$  or  $32^{\circ}\text{F}$ )—is an important cold season  
54 weather-climate variable. AFDD determines the amount of freezing energy available in the  
55 air to grow surgical ice on lakes, and consequently analytical studies often estimate the  
56 thickness of lake ice cover to be roughly proportional to the square root of the winter  
57 AFDD (Lepparanta, 2014). However, the impacts of wintertime AFDD variations on lakes  
58 may not be limited to the cold season. For example, springtime ice-out dates for Maine  
59 (USA) lakes are linked to wintertime AFDD thresholds (Beyene and Jain, 2015).

60 The prevailing winter climate, including the AFDD patterns over North America,  
61 has been shown to be sensitive to phases of El Niño-Southern Oscillation (ENSO), a  
62 coupled oceanic-atmospheric phenomenon in the tropical Pacific that affects weather and  
63 climate worldwide (e.g., Bonsal et al. 2001; Assel et al. 2004; Bai et al. 2012). For instance,  
64 during the 1997/98 El Niño event (warm phase of ENSO), northern US and southern  
65 Canada recorded one of their lowest winter AFDDs such that it resulted in the least  
66 extensive ice-cover in the Great Lakes over the past century. However, the severity and  
67 spatial extent of the North American weather and climate anomaly patterns associated with  
68 El Niño events is neither alike nor is it linearly opposite to that of La Niña (cold phase of  
69 ENSO) events (e.g., Wyrski, 1975; Hoerling and Kumar, 1997; Hoerling et al. 1997).  
70 Studies have shown that such discrepancies may arise from differences in the location and  
71 amplitude of their signature SST anomalies in the tropical Pacific as variations in the



72 location of the warmest waters (SST>27.5C) in the tropical Pacific generate differential  
73 atmospheric wave trains responsible for climate variability worldwide (e.g., Barsugli and  
74 Sardeshmukh, 2002; Hoerling and Kumar, 1997). Furthermore, Beyene and Jain (2017)  
75 showed that the sensitivity of North American winter temperatures to diverse ENSO  
76 flavours is not uniform, both regionally and across different parts of the empirical  
77 probability density function (EPDF). In the present context, a salient question is: to what  
78 extent do distinct El Niño flavours affect North American lake ice-out dates through their  
79 differential effect on the (EPDF of) winter AFDD? Two aspects of current and future  
80 ENSO variability further motivate the above noted line of inquiry: (a) five-fold increase in  
81 the frequency of a “new variant” of ENSO is being projected under anthropogenic climate  
82 change (e.g. Yeh et al. 2009; Cai et al. 2014), (b) ENSO-based climate forecasts on  
83 seasonal and longer lead-times have proven to be reliable (Hoskins, 2013). To this end, this  
84 study aims to develop location specific risk functions for North American winter AFDD,  
85 that incorporate as covariates ENSO indices that capture the location and amplitude of  
86 tropical Pacific SST anomalies, in order to estimate ENSO-related changes in the relative  
87 occurrence probability of early/late lake ice out events in North America. In this study, the  
88 term occurrence probability is used interchangeably with risk and likelihood.

89 Past lake ice studies often assessed ENSO-induced changes in lake ice season by  
90 characterizing the response of local meteorological variables (relevant to lake ice evolution)  
91 to large-scale climate patterns using traditional statistical methods such as linear regression  
92 and averaging of sub-samples. However, analyses employing these methods offer limited  
93 insight, as they primarily measure the shift in the conditional mean and not the conditional  
94 tails of the distribution, where climate-related thresholds in lakes usually reside. This study

95 thus employs quantile functions, first proposed by Koenker and Bassett (1978), to  
96 investigate the response of North American winter AFDD, across its variability range, to  
97 the amplitude and location of tropical Pacific SST warming/cooling, linked to ENSO  
98 events. This approach provides a functional framework to estimate the winter AFDD  
99 conditioned on ENSO indices with three important features: (a) no distributional  
100 assumption, (b) quantification of differential sensitivity across quantiles, and (c) resistance  
101 to outlier effects.

102 Beyene and Jain (2017) have shown that the change in the conditional risk of North  
103 American winter temperatures due to ENSO flavors varies both regionally and across  
104 different temperature quantiles. This study extends their work and aims to quantify ENSO  
105 related changes in North American lake ice out dates by characterizing its effect on winter  
106 AFDD variability. Two key tasks in this regard are as follows:

- 107 (1) Quantify the nature of relationships between lake ice and winter AFDD variability,  
108 based on observational records for a select group of lakes across North America.
- 109 (2) Estimate ENSO-related changes in the relative likelihood of early/late lake ice out  
110 events for eight North American lakes—location-specific risk functions for North  
111 American winter AFDD that incorporate ENSO indices as covariates are developed.

## 112 **2. Data and Methods**

113 *Lake Ice-out (off) Dates:* Lake ice-out date refers to the date when winter ice completely  
114 disappears from the lake surface. In this study, eight North American lakes (see Figure 1  
115 for lake locations) that freeze during the winter were selected and their historical lake ice-

116 out dates from 1950-2010 were downloaded from the following electronic databases:  
 117 Global Lake and River Ice Phenology Database (at National Snow and Ice Data Center) and  
 118 Lake Ice Clearance and Formation dataset (at Niwot Ridge Long Term Ecological Research  
 119 Center). In Supplementary Table 1, geomorphological data and site of observation for ice  
 120 out dates is provided for the eight selected lakes.

121 *North American Winter AFDD*: Time series of gridded, daily mean temperature data for  
 122 North America from 1951-2010 were derived from HadGHCND dataset (Caesar et al.  
 123 2006), which provides station-based, daily observations of average temperature data on a  
 124  $2.5^\circ \times 3.75^\circ$  grid resolution. The year-to-year winter AFDD for North American fields were  
 125 then calculated as the daily degrees below freezing ( $0^\circ\text{C}$ ) summed over the total number of  
 126 days from December to February that the daily average temperature was below freezing:

$$127 \quad AFDD = \sum_{i=1}^{i=n} (T_0 - T_i) \Delta t, \quad T_0 > T_i, \quad (1)$$

128 where  $\Delta t$  is the time interval ( $\Delta t = 1$  day),  $n$  is the number of days from December to  
 129 February months ( $n = 90$  or  $91$ ),  $T_i$  is the daily mean temperature ( $^\circ\text{C}$ ) and  $T_0$  is the freezing  
 130 temperature for water ( $T_0 = 0^\circ\text{C}$  or  $32^\circ\text{F}$ ). Lake ice occurs predominantly in regions with  
 131 regular occurrence of sub-freezing temperatures and wintertime AFDD. Climatological  
 132 winter AFDD patterns over North America (Figure 1a, b) indicate that regions with pole  
 133 ward of  $35^\circ\text{N}$  show appreciable below-freezing temperatures; this region will be the focus  
 134 of investigation in the remainder of this study.

135 *Relationship between AFDD and lake ice thickness*: Lake ice formation and growth results  
 136 from the dynamical heat balance at lake surface. (Lepparanta 2014). Given that the surface

137 air temperature strongly relates to major energy fluxes from lake to atmosphere, analytical  
 138 studies often use the degree-day method— first derived by Stefan (1891) — to approximate  
 139 the thickness of winter ice formed on lake surface. In general, in a degree-day model, ice  
 140 growth ( $h$ ) in inches, is modelled as a function of the square root of the accumulated  
 141 freezing degree-days ( $AFDD$ )

$$142 \quad h = C\sqrt{AFDD} \quad (2)$$

143 where  $C$  is a coefficient that accounts for local snow and atmospheric conditions and  
 144  $AFDD$  is in Degree-Day Fahrenheit (DDF) (e.g., Assur 1956). In Supplementary Analysis 2  
 145 section, we provide a detailed exposition of this physical basis of the relationship noted  
 146 above.

147 *ENSO Indices:* The emergence, type and strength of El Niño /La Niña events are often  
 148 based on areal averaged SST indices for four regions in the tropical Pacific: Niño 1+2, Niño  
 149 3, Niño 3.4 and Niño 4 (see supplementary Figure S1a). In this study, time series of  
 150 monthly, spatially averaged SSTs for the four Niño regions from 1951-2010 were collected  
 151 from a dataset prepared by NOAA’s Climate Prediction Center, based on extended,  
 152 reconstructed sea surface temperature (ERSST) V4 dataset. Time series of winter Niño SST  
 153 indices from 1951-2010 were then computed by averaging the December to February SST  
 154 index for each Niño region (see Supplementary Figure S1b).

155 Geographical distributions of ENSO-related tropical Pacific SST anomalies  
 156 (warming or cooling relative to long-term averages) have been identified as important  
 157 contributors to the spatial patterns and severity of climatic impacts in remote regions. Thus,

158 it is critical to identify a small set of ENSO indices that best represent the detailed pattern  
159 of SST warming or cooling in the tropical Pacific. In this study, Principal Component  
160 Analysis was performed on the time series of mean winter SST indices of the four Niño  
161 regions from 1951-2010 (see Supplementary Analysis 1). The resulting pair of indices  
162 (Principal Component 1 and 2, hereafter referred as PC1 and PC2) account for 99.8% of the  
163 total variance in the ENSO historical record (PC1 = 89% and PC2 =10.8%). While PC1 and  
164 PC2 time series comprehensively characterize the temporal variations in ENSO over the  
165 past six decades, the spatial loadings linked to these PCs offer helpful interpretation of the  
166 tropical Pacific warming and cooling patterns associated with ENSO events (see  
167 Supplementary Figure S2). PC1 loadings across the four Niño regions are of the same sign  
168 suggesting synchronous wintertime SST variation across all Niño regions (see  
169 Supplementary Table 2b and Supplementary Figure S2b). PC2 loadings are characterized  
170 by an east-west dipole pattern with the wintertime SSTs in Niño-1+2 (eastern Pacific)  
171 region varying out of phase with that of Niño-3.4 and Niño-4 (Central Pacific) regions  
172 (Supplementary Figure S2c). Beyene and Jain (2017) and others have showed that the joint  
173 indices of PC1 and PC2 allow characterization of the amplitude and location of maximum  
174 TP SST anomalies associated with diverse El Niño/La Niña events (see Supplementary  
175 Analysis 1). Therefore, PC1 and PC2 indices are used as covariates/predictors in the  
176 quantile regression pursued in this study. Finally, as noted in the previous section, recent  
177 improvements in the understanding on ENSO flavors imply distinct patterns of climatic  
178 impacts across North America, and projected trends for the 21<sup>st</sup> century reveal dramatic  
179 shifts in ENSO frequency—the associated risk to environmental variables such as lake ice  
180 remains unclear.

181 *Quantile Regression*: Historical winter AFDD variability at a particular location can be  
 182 summarized based on a frequency distribution or probability density function (PDF).  
 183 Characteristic AFDD values that correspond to specific quantiles (representing non-  
 184 exceedance probability) can be obtained from the PDF. For instance, the AFDD value for  
 185 the 0.25<sup>th</sup> quantile is exceeded 75% of the time. An extension of this approach allows  
 186 modelling of quantiles based on covariates or predictors (for example, ENSO conditions)  
 187 that modulate the conditional quantile functions for the target variable (in our case, AFDD).  
 188 In its general form, quantile regression (Koenker and Hallock 2001) affords conditional  
 189 quantile estimates for each quantile, and as such, conditional PDF. These estimates are  
 190 superior to ones from linear regression, wherein covariate effects are restricted to affect on  
 191 the mean of the target variables. Example applications of quantile regression in lake studies  
 192 include Bissinger et al. (2008), Fielding (2013), and Xu et al. (2015).  
 193 In this study, the quantile regression approach is used to model and predict the linear  
 194 response of North American winter AFDDs, across all or selected quantiles, to ENSO  
 195 indices ( $X_i$ ). Mathematically, this can be expressed as

$$196 \quad AFDD(\tau) = \beta_0^{(\tau)} + \beta_1^{(\tau)}PC1 + \beta_2^{(\tau)}PC2 \quad (3)$$

197 where  $\beta_0^{(\tau)}$  is the intercept, and  $\beta_1^{(\tau)}$  and  $\beta_2^{(\tau)}$  are the slope coefficients for  
 198 PC1 and PC2 patterns at  $\tau^{\text{th}}$  quantile. The regression parameters  $\beta^{(\tau)}$  are obtained by  
 199 solving for minimization of the sum of weighted absolute residuals. The quantile regression  
 200 implementation in the R computing environment (Koenker, 2017) is employed to provide  
 201 the optimizing algorithm to estimate  $\beta^{(\tau)}$  using linear programming techniques.

202 Estimation of conditional winter AFDD quantiles requires fitting of curves across each  
203 quantile independently and as such generating multiple conditional winter AFDD quantile  
204 functions may yield quantile curves that cross or overlap, creating an invalid distribution.  
205 To alleviate the crossing problem in quantile regression, a procedure introduced by Bondell  
206 et al. (2010), which imposes a non-crossing constraint, is applied. The statistical  
207 significance for parameter estimates,  $\beta^{(\tau)}$  in the conditional winter AFDD functions were  
208 assessed by constructing the confidence interval using the wild bootstrap method, an  
209 approach that is almost unaffected by residual heterogeneity (Feng et al. 2011).

### 210 **3. Results**

#### 211 *3.1 Winter AFDD and North American Spring Lake Ice-out Dates*

212 Empirical and theoretical rationales are needed to establish the import of seasonal winter  
213 (December-February) AFDD on North American lake ice season. To this end,  
214 Supplementary Analysis 2 presents a synopsis of the theoretical-physical basis underlying  
215 AFDD-lake ice linkages. This section on the other hand, offers empirical findings by  
216 analyzing the observed response of spring lake ice-out dates to their antecedent winter  
217 AFDDs for eight North American lakes (see Figure 1a). Here, the efficacy of winter AFDD  
218 in conditioning the spring lake ice out dates was examined using non-parametric kernel  
219 regression approach, as the functional relationship between winter AFDD and spring ice-  
220 out dates is unknown and may vary across lakes. Kernel regression method (Silverman  
221 1986) is based on a smoothing approach that is locally adaptive, thus allowing for the  
222 estimation of linear and nonlinear relationship from data. The degree of smoothing depends

223 on the bandwidth, which is selected based on a minimization of integrated error (Bowman  
224 and Azzalini, 1999). In the context of ice-out and winter AFDD relationship, of particular  
225 interest is the diagnosis of nonlinearity and potential break points in the relationship (akin  
226 to thresholds).

227         Results of this analysis show that for all selected lakes, there is a positive (direct)  
228 relationship between winter AFDD and spring ice-out dates, which implies that winters  
229 with relatively low (high) winter AFDDs are generally related to earlier (later) than normal  
230 lake ice-out dates the following spring (see Figure 1c-j). However the degree of sensitivity  
231 of spring ice-out dates to winter AFDDs in these lakes varies both spatially and across  
232 different winter AFDD quantiles. For instance, contrasting the overall slope of the winter  
233 AFDD regression line across the eight lakes indicate that the response of spring ice-out  
234 dates to the antecedent winter AFDD variability is relatively stronger at Lake Superior  
235 (USA) and Damariscotta Lake (USA) as compared to those at Lake Albion (USA) and  
236 Long Lake (Canada). This implies that the strength of association between spring ice-out  
237 dates and the antecedent winter AFDDs for North American lakes shows geographical  
238 variation and locally, is also likely to be modulated by other factors such as morphometry,  
239 elevation, and continentality. On the other hand, examining the response of spring ice-out  
240 dates of the eight lakes across different winter AFDD quantities reveals that unusually low  
241 /high winter AFDDs are strongly related to early/late spring ice-out dates. For instance, for  
242 Damariscotta Lake, 5 of the 6 winters with AFDD less than 200 Degree Day Celsius (DDC)  
243 ( $\tau \leq 0.30^{\text{th}}$ ) are associated with ice-out dates earlier than April 3<sup>rd</sup> (see figure 1H). Similarly



244 for Lesser Slave Lake (Canada), 5 of the 6 winters with AFDD less than 2270 DDC ( $\tau \leq$   
245 0.28<sup>th</sup>) are linked to ice out dates that occurred prior to May 15<sup>th</sup> (see figure 1D).

246 These findings on the presence of winter AFDD quantities that correspond to  
247 early/late spring ice-out dates for North American lakes is consistent with the findings  
248 reported in Beyene and Jain (2015). This implies that the efficacy of ENSO events in  
249 modulating the variability of ice-out dates in lakes depends on their effect on the  
250 occurrence of winter AFDDs associated with ice-out dates. Thus, characterization of  
251 ENSO-related change in risk of early/late ice dates requires an understanding of the  
252 relationship between different El Nino (or La Nina) events and winter AFDD at specific  
253 quantiles, as well across the entire winter AFDD distribution. It should be noted that for  
254 studied lakes, the degree of coherence between winter AFDD and spring ice-out dates can  
255 generally be assumed to be independent of spring temperature conditions, as there is no  
256 significant ( $p < 0.1$ ) correlation between winter and spring AFDD for almost all North  
257 American regions (see Supplementary Figure S4).

### 258 ***3.2 ENSO Diversity and North American Winter AFDD Variability***

259 Differences in the location of peak ENSO-related Sea Surface Temperature (SST)  
260 warming/cooling in the Tropical Pacific (TP) contribute to the observed variability in  
261 ENSO-related climate patterns in North America (e.g., Hoerling and Kumar, 1997). To  
262 illustrate this difference in the context of North American winter AFDD, five years were  
263 selected where by majority agreement of different ENSO identification methods (EP/CP  
264 method, Niño3/4 method, EMI method and regression-EOF method) have been determined  
265 as Central Pacific (CP) El Niño (1969, 1988, 1995, 2003, 2005, 2010), Eastern Pacific (EP)

266 El Niño (1973, 1983, 1987, 1998, 2007) and La Niña events (1956, 1971, 1974, 1976, 1989)  
267 (see Supplementary table 1). It should be noted that our use of EP and CP El Niño  
268 terminology in this study serves only to contrast the site of peak SST warming in TP  
269 between the two El Niño patterns, and is by no means implying that these patterns are  
270 distinct modes of El Niño. The composite TP winter SST anomaly (departure from the  
271 long-term average) pattern for the five CP El Niño events selected features peak SST  
272 warming confined in the central TP regions (Niño3.4 and Niño4 regions) flanked by cooler  
273 than normal SSTs on both sides of the equatorial Pacific (see Figure 2a bottom). While  
274 there is some inter-event differences, the pattern of North American winter AFDD  
275 variability pattern corresponding to CP El Niño events can broadly be characterized as  
276 southeast-northwest dipole pattern, where there is relatively strong increase in the seasonal  
277 winter AFDD (colder temperatures) over the Midwest and northeast US regions and  
278 decrease in winter AFDD (warmer temperatures) over western US and Canadian regions  
279 and northern edges of Canada (see Figure 2a top). In contrast, the location of maximum  
280 SST warming in the TP during EP El Niño winters is concentrated in eastern TP extending  
281 from the western coast of South America to the regions east of the dateline (Niño1+2 &  
282 Niño 3 regions) (see Figure 2b). Moreover, these events are associated with a significant  
283 decrease of winter AFDD over much of North America (except for the Pacific US regions  
284 and Baffin Island). These results illustrate that the location of maximum SST warming in  
285 the tropical Pacific has important implication on the impact of individual El Niño events on  
286 the winter AFDD over US and Canada. On the other hand, the composite TP winter SST  
287 anomaly pattern for the five La Niña events exhibits peak SST cooling over central-eastern  
288 equatorial Pacific (Niño3 and Niño4 regions). Moreover, the North American winter AFDD

289 anomaly patterns related to these events generally features a northwest-southeast dipole  
290 pattern with a relatively strong increase in winter AFDD over western Canada and Alaska  
291 and decrease in winter AFDD over the Southeast US states. These results reveal the effect  
292 of La Niña events on the winter AFDD of various North American regions is not a mirror  
293 opposite to that of El Niño events. They also establish the significance of tropical Pacific in  
294 producing non-linearity in the response of North American winter AFDD to opposite  
295 phases of ENSO.

296 In summary, the above findings show that the ENSO-winter AFDD relationship for  
297 North America varies with the location of peak ENSO-related SST warming and/or cooling  
298 in the TP. In other words, the efficacy of El Niño (or La Niña) events in modulating the  
299 conditional winter AFDD distribution for North American regions shows spatial variation.  
300 Consequently, in the face of EP or CP El Niño/La Niña episodes, the likelihood associated  
301 with various AFDD magnitudes, including the ones that correspond to early/late spring ice-  
302 out dates in North American lakes, is marked by differential sensitivities. Quantile  
303 regression framework offers conditional risk estimates of AFDD at a location as well as  
304 regional scale.

### 305 ***3.3 ENSO Patterns and Lake Ice Season Risk Assessments***

306 It was noted in earlier sections that there are winter AFDD quantities that correspond to  
307 early/late spring ice-out dates for North American lakes. The efficacy of quantile functions  
308 in generating AFDD quantiles conditioned on ENSO indices can thus offer usable risk  
309 estimates for unusually early/late ice-out events in these lakes. For instance, figure 3a  
310 shows that for Lake Superior, winters with AFDDs less than 820 Degree-day Celsius

311 (DDC) ( $\tau < 0.31^{\text{th}}$ ) are strongly associated with spring lake ice-out dates prior to March  
312 30<sup>th</sup>, and according to the climatology, the occurrence probability of such “mild winters” is  
313 0.30. Please note that the method used here for determining the winter AFDD threshold is  
314 highly subjective and as such serves only for illustrative purposes only. To estimate the  
315 change in the conditional risk of early lake ice-out dates at Lake Superior due to ENSO  
316 patterns, a set of quantile functions for winter AFDD (that incorporate ENSO indices as  
317 covariates) were fitted at  $\tau = 0.01$  intervals over the quantile range ( $0.01 < \tau < 0.99$ ) and  
318 these function were used to compute winter AFDDs at the respective quantiles for sample  
319 combination of PC1-PC2 indices. Figure 3b shows the resulting conditional winter AFDD  
320 distribution as well as conditional risk of winter AFDDs less than 820 DDC for  
321 archetypical ENSO flavors (derived as centroids of PC1-PC2 index for the five selected EP,  
322 CP El Niño and La Niña events mentioned in the first result section). From these, it can be  
323 observed that during archetypical EP El Niño events, the likelihood of mild winters that  
324 engender early ice-out dates at Lake Superior increases by 2.16 times relative to that of the  
325 climatology (probability = 0.31). During typical CP El Niño pattern however, there is no  
326 significant change in the occurrence probability of early ice out dates at Lake Superior  
327 relative to that of the climatology. Contrary to the traditional assumption, this result  
328 highlights that the effect of different El Niño flavors on North American lake ice-out dates  
329 are not alike. Figure 3c extend the results in figure 3b to depict the change in risk (relative  
330 to that of the climatology) of early ice-out dates for sample combinations of PC1 and PC2  
331 indices. Broadly speaking, the conditional risk of early ice-out dates at Lake Superior  
332 increases from region of negative PC1 and positive PC2 to a region of positive PC1 and

333 negative PC2. This means that strong EP El Niño patterns ( $PC1 > 2$  &  $PC2 < 0$ ) are related  
334 to an increase the relative likelihood of early ice-out dates at Lake Superior by 1.2 - 2.5  
335 times that of the climatology, while strong CP El Niño events ( $PC1 > 1$  &  $PC2 > 0$ )  
336 correspond to a rise in the relative risk of early ice out dates by 0.9-2.4 times. On the other  
337 hand, La Niña events ( $PC1 < -1.5$  &  $PC2 < 0$ ) reduce the relative occurrence probability of  
338 mild winters by 0.6-1.

339 Diversity in the influence of different ENSO patterns on North American lake ice-out dates  
340 can be illustrated by contrasting the change in the likelihood of mild winters that produce  
341 early ice-out dates, due to the three archetypical ENSO patterns, for the eight North  
342 American lakes. Results reveal that the effect of ENSO pattern on the timing of North  
343 American spring lake ice-out dates varies both spatially and for different ENSO events (see  
344 Figure 4). For seven of the eight lakes, the archetypical EP El Niño pattern increases the  
345 likelihood of mild winters that correspond to early ice-out dates, by 1.5-2.8 times to that of  
346 the climatology, while for Deadman's Pond the occurrence probability of such winters  
347 decreases by 0.63 times relative to the climatology. In contrast, at Damariscotta Lake and  
348 Deadman's Pond, typical CP El Niño pattern decreases the likelihood of mild winters that  
349 are associated with early ice out dates, by 0.4-0.8 times to that of the climatology, while for  
350 the other six lakes it has modest or no effect on the risk of such winters. On the other hand,  
351 for Lake Albion (Deadman's Pond), archetypical La Niña pattern reduces (increases) the  
352 occurrence probability of mild winters by 0.46 (1.2) times to that of the climatology, while  
353 for the other six lakes, it is associated with modest or no changes in risk of early ice out  
354 dates. These results taken together show that for North American lakes, (a) the effect of EP  
355 El Niño on the timing of ice-out dates is quite distinct to that of CP El Niño from local-to-

356 regional scale, (b) El Niño related changes in the timing of spring ice-out dates is not a  
357 linear opposite to that of La Niña events. As discussed in earlier sections, these effects stem  
358 from the asymmetry in the regional AFDD patterns associated with El Niño/La Niña  
359 flavors and distinctness of AFDD thresholds for ice-out dates among local lakes.  
360 Supplementary figure S6-S10 depicts the wintertime AFDD quantities that correspond to  
361 early ice out date in lakes and the results of the conditional risk analysis for sample  
362 combinations of PC1 and PC2 for the seven other lakes.

#### 363 **4. Discussion and Summary**

364 ENSO-related warming/cooling in the tropical Pacific sea surface temperatures cause  
365 systematic shifts in the North American wintertime Accumulated Freezing Degree-days  
366 (AFDD) patterns. Winter AFDD governs the thermal flux between lake and atmosphere to  
367 grow lake ice, and early/late spring ice-out dates have been sensitively linked to seasonal  
368 winter AFDD thresholds. Consequently, changes in the magnitude and frequency ENSO  
369 has the potential to cause shifts and transitions in the ice regime of North American lakes.  
370 Our analysis of the response of spring ice-out dates to winter AFDD for select North  
371 American lakes reveals two important features. One is that for North American lakes, the  
372 relationship between winter AFDD and spring lake ice-out dates can be characterized from  
373 quasi-linear to highly non-linear. Second, in a number of these relationships, there are  
374 AFDDs (thresholds) that are strongly associated with specific ice out dates. Thus, the  
375 conditional quantile regression approach developed in this study allows a detailed  
376 characterization of quantile-specific ENSO-AFDD that can be readily used to estimate risk  
377 functions for AFDD and lake ice out conditioned on ENSO. Results for seven out of the

378 eight North American lakes show that typical Eastern Pacific (EP) El Niño pattern is  
379 associated with an increase in the risk of low winter AFDDs (that produce early ice-out  
380 dates in these lakes) by 1.5-2.8 times to that of the climatology, while the typical Central  
381 Pacific (CP) El Niño pattern corresponds to a decrease or no significant change in the  
382 likelihood of early ice-out dates in these lakes. On the other hand, for Deadman's Pond  
383 (Lake Albion) the archetypical La Niña pattern induces an increase (decrease) the  
384 occurrence probability of early ice out dates by 1.2 (0.46) times relative to that of the  
385 climatology. To summarize: (a) the effect of CP and EP El Niño on the timing of spring  
386 ice-out dates of North American lakes is distinct from local-to-regional scale, (b) for North  
387 American lakes, the change in the timing of spring ice-out dates due to El Niño and La  
388 Niña patterns is not linearly opposite. In conclusion, we offer the following observations  
389 and discuss emerging research directions:

- 390 1. This work broadens current understanding of ENSO-related AFDD  
391 teleconnections for North America. In doing so, the relative contributions of  
392 ENSO flavors (delineated as the two leading pattern of tropical Pacific SSTs) in  
393 modulating AFDD distribution as a whole, and select AFDD thresholds  
394 (associated with lake ice-out dates) for North American regions was quantified..  
395 Detection and evolution of ENSO events in the tropical Pacific is a well  
396 understood subject and as such, magnitudes of ENSO events are estimable up to 9  
397 months in advance (e.g. Ramesh and Murtugudde, 2012; Hoskins, 2013). These  
398 imply that the ENSO-related conditional risk functions developed here pave the

399 way for use of seasonal and longer-lead ENSO forecasts that can be profitably  
400 used to anticipate shifts in lake ice out dates.

401 2. The quantile regression risk framework advanced in this study, while specific to  
402 lake ice out, is applicable to other lake variables to assess climate-related risk and  
403 vulnerability. While a linear approach was taken here, nonlinear and non-  
404 parametric approach can be used to model complex relationships (for example,  
405 ones involving lake chemistry).

406 3. Changing weather/climate patterns reflect trends and inter-annual variability (for  
407 example, due to ENSO). Resulting seasonal temperatures can disrupt the lake  
408 phenology and linked processes, species dynamics and succession, and nutrient  
409 loading and mixing characteristics. For instance, for temperate and arctic North  
410 American lakes, winter climate variability has directly or indirectly been shown to  
411 affect ice cover phenology and extent (e.g. Bai et al. 2012; Beyene and Jain  
412 2015), water temperatures (e.g. Austin and Colman 2007), onset of stratification  
413 period (e.g. Winder and Schindler 2004), seasonal plankton composition,  
414 abundance and succession (e.g. Goldman et al. 1989; Hampton et al. 2017), fish  
415 population (e.g. Farmer et al. 2015) and seasonal geo-chemical dynamics (e.g.  
416 Joung et al. 2017; Powers et al. 2017). In a changing climate, successful  
417 conservation and restoration of lake ecosystems can benefit from climate-based  
418 risk framework presented here, thus affording pinpointed estimates of trends and  
419 transitions in lake variables. Finally, improved understanding and prediction of  
420 lake and river ice conditions has important environmental and socio-economic



421 (e.g. recreational, hydro-power generation, cultural, commercial) implications, a  
422 point underscored in recent studies (e.g., Prowse et al. 2011; Durnford et al.,  
423 2017).

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576 **List of Manuscript Body Tables**

577 Table 1: Ratio of conditional likelihood of selected winter AFDDs over lakes due to ENSO  
578 events, to that of the unconditional. Results are computed using the same techniques as in  
579 figure 3b.

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598 Table 1: Ratio of conditional likelihood of selected winter AFDDs over lakes due to ENSO  
 599 events, to that of the unconditional. Results are computed using the same techniques as in  
 600 figure 3b.  
 601

Lake	Ice out dates corresponding to winter AFDD		Unconditional probability of W* for the 1951-2010 period	Conditional risk relative to the Unconditional probability		
	Winter threshold (W*) in DDC units	Ice-out Date corresponding to W*		Eastern Pacific El Niño	Central Pacific El Niño	La Niña
Damariscotta	200	3-April	0.14	1.57	0.78	0.93
Superior <sup>#</sup>	820	31-March	0.31	2.16	1.06	0.83
Winnipeg	2015	13-May	0.26	3.3	0.43	1.06
Lesser Slave	2170	13-May	0.28	1.67	0.93	0.82
Dease	2170	28-May	0.1	1.7	1.2	0.5
Deadman's Pond	1735	3-May	0.3	0.63	0.7	1.2
Long	2730	26-May	0.2	2.5	0.85	0.7

602 AFDD- Accumulated Freezing Degree days

603 DDC- Degree-day Celsius

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## 616 **List of Manuscript Body Figures**

617 Figure 1: Climatology of winter Accumulated Freezing Degree Days (AFDD) over North  
 618 America and its relationship with lake ice-out dates. North American map of the (a) mean,  
 619 (b) standard deviation of winter AFDDs from 1951-2010. Contour intervals for the mean  
 620 and standard deviation winter AFDD are set at 300 and 40 Degree-day Celsius (DDC)  
 621 respectively. The red coloured polygons represent the location of the eight selected lakes.  
 622 Plotting lake ice-out dates as a function of winter AFDD at (c) Dease Lake (d) Lesser Slave  
 623 Lake (e) Lake Winnipeg (f) Lake Albion (g) Deadman's Pond (h) Damariscotta Lake (i)  
 624 Lake Superior (j) Long Lake. The filled/unfilled polygons in each scatter plot represent the  
 625 ice out date as a function of winter AFDD for each lake. The red line denotes locally  
 626 averaged lake ice out date conditioned on the winter AFDD, and is computed using non-  
 627 parametric kernel regression method. The blue shadings designate the 90% confidence band  
 628 for a linear model.

629 Figure 2: Composite maps of tropical Pacific winter SST warming/cooling and associated  
 630 North American winter Accumulated Freezing Degree-days (AFDD) anomalies for select  
 631 five (a) Central Pacific (CP) El Niño (b) Eastern Pacific (EP) El Niño (c) La Niña events.  
 632 These events were chosen by majority consensus across different identification methods in  
 633 the literatures (see Supplementary Table 3). Anomalies are computed as departure from the  
 634 1951-2010 average and contour intervals for winter AFDD and SST anomalies are 40  
 635 Degree day Celsius (DDC) and  $0.25^{\circ}$  Celsius respectively. Stippled areas denote regions  
 636 where the departure is significant at 90% confidence level based on two-tailed re-sampling  
 637 tests.

638 Figure 3: Risk estimates for winter Accumulated Freezing Degree-day (AFDD) quantities,  
 639 corresponding to spring ice-out dates earlier than April 1<sup>st</sup> at Lake Superior, conditioned on  
 640 different El Niño /Southern Oscillation patterns. (a) Scatter plot for spring ice-out dates at  
 641 Lake Superior as a function of the antecedent winter AFDD. The grey unfilled circles  
 642 denote the winter AFDD associated with observed ice out dates. The purple line represents



643 locally averaged lake ice-out dates conditioned on the winter AFDD, and is computed using  
 644 non-parametric kernel regression method. The blue shadings denote the 90% confidence  
 645 band for computed regression line. (b) Conditional winter AFDD distribution at Lake  
 646 Superior associated with the three archetypical ENSO patterns: CP El Niño (blue), La Niña  
 647 (green) and EP El Niño (red). The grey area represents part of the conditional distribution  
 648 less or equal to 820 Degree-day Celsius (DDC). The conditional winter AFDD distribution  
 649 curves for typical ENSO patterns was constructed by generating conditional quantile  
 650 functions for estimating winter AFDD at  $\tau = 0.01$  intervals over the quantile range ( $0.01 < \tau$   
 651  $< 0.99$ ), followed by estimation of winter AFDD quantiles at the centroid of five selected  
 652 samples of ENSO flavours in the PC1-PC2 phase space. (c) Contour surface plot of  
 653 estimated conditional risk for winter AFDD at Lake Superior to be less or equal to 820  
 654 DDC, relative to the unconditional (climatology). The dark filled circles represent the PC1-  
 655 PC2 indices for the three archetypical ENSO patterns, while the grey polygon represents  
 656 the convex hull – region containing observed PC1-PC2 values. The colour key for ratio of  
 657 risk conditioned on PC1-PC2 values is given at the bottom.

658 Figure 4: Risk estimates for winter Accumulated Freezing Degree-days (AFDD) quantities  
 659 (thresholds), corresponding to early ice-out dates for selected North American lakes,  
 660 conditioned on three archetypical ENSO patterns. At each lake, the blue, green and red  
 661 curves denote the conditional winter AFDD distribution associated with Central Pacific  
 662 (CP) El Niño, La Niña and Eastern Pacific (EP) El Niño respectively, while the black curve  
 663 represents the unconditional winter AFDD distribution for the 1951-2010 period. The steps  
 664 by which the conditional distributions are generated are given in the caption for figure 3b.  
 665 The grey area signifies part of the conditional distribution less or equal to specific AFDD  
 666 threshold (broken black line). The confidence intervals for risk estimates was determined  
 667 by computing the occurrence probability of each year conditioned on its PC1-PC2 index  
 668 and determining the 5<sup>th</sup> and 95<sup>th</sup> percentile from the time series of risk estimates.  
 669 Conditional non-exceedance probability (risk) estimates in bold are significant at 10%  
 670 significance level.

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