THE FUTURE OF LAKE ICE: DRIVERS, TRENDS, AND PROJECTIONS OF ICE PHENOLOGY AND ICE QUALITY

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Abstract

Lake ice is changing rapidly due to climate warming, with significant ecological and societal impacts. Since lake ice provides vital ecosystem services and regulates lake conditions, understanding changing lake ice patterns is critical for managing future risks to ecosystems and communities. However, substantial knowledge gaps exist in lake ice research, including the underrepresentation of small lakes in large-scale ice phenology assessments, the lack of large-scale projections of lake ice quality, and a limited understanding of how locally and regionally altered human landscapes may influence ice dynamics. This thesis addresses these gaps by: (1) forecasting ice phenology with extensively involving representation of lakes (<1 km^2) across the Northern Hemisphere (Chapter 2); (2) projecting ice quality, specifically black and white ice thickness, and implications for human safety (Chapter 3); and (3) assessing how local and regional drivers influence ice dynamics (Chapter 4). Chapter 2 reveals that lakes are losing ice faster than previously reported, with a sharp drop in ice-cover duration in the late twentieth century. Including abundant but underrepresented small lakes in predictive models improves forecasts of ice phenology under future climate scenarios. Chapter 3 extends this work by providing the first large-scale assessment of lake ice quality, indicating that warming will reduce total ice thickness and increase the proportion of weaker white ice, heightening hazards for winter travel and other activities. Chapter 4 systematically evaluates how landscape and human pressures affect ice phenology at regional and local scales, shaping ice dynamics in northern U.S. lakes. Collectively, this thesis advances our understanding of lake ice by projecting how both ice timing and ice structure are likely to change through the end of the century and clarifying the extent to which regional and local landscape characteristics may complement broader climate mitigation efforts. These findings highlight lake ice as both a sensitive indicator of climate change and a critical component of freshwater ecosystems and northern livelihoods, underscoring the urgent need for coordinated global, regional, and local responses to preserve the ecological and societal benefits of seasonal lake ice.

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Chapter 1: General introduction

Lakes are widely regarded as sentinels of climate change as they respond rapidly to variations in atmospheric conditions, displaying signals of climatic change across seasons and years (Adrian et al., 2009; Mueller et al., 2009). Among the many indicators of environmental change observed in lakes, seasonal ice cover remains an essential climate variable due to its widespread ecological and societal importance (Woolway et al., 2020). Lake ice regulates the exchange of energy and gases between the atmosphere and aquatic systems, shaping both ecosystem processes and human activities that depend on seasonal ice cover (Hampton et al., 2024).

When lakes freeze, the formation of ice cover fundamentally alters lake physics and ecology. By covering the air-water interface for extended periods, ice alters heat exchange, limits wind-driven mixing, and restructures seasonal biogeochemical dynamics (Cavaliere et al., 2021; Hampton et al., 2017; Jansen et al., 2021). These physical changes influence numerous biological processes, including under-ice oxygen dynamics (Barrett & Wrona, 2025; Huang et al., 2021; Klanten et al., 2023; Zdorovennova et al., 2021), nutrient cycling (Cavaliere & Baulch, 2018, 2019, 2021), and food-web interactions (Hampton et al., 2015; Hébert et al., 2021; Hrycik & Stockwell, 2021; Rounds et al., 2025). Winter conditions can also influence ecosystem function beyond the ice cover period, affecting the timing and magnitude of spring and summer productivity (Cavaliere et al., 2021; Feiner et al., 2022; Primicerio et al., 2007). Consequently, lake-ice plays an essential role in regulating seasonal ecological dynamics in dimictic systems.

Beyond its ecological importance, stable and predictable ice cover provides significant ecosystem services to human communities (Knoll et al., 2019; Magnuson & Lathrop, 2014). Many northern populations rely on frozen lakes for transportation, recreation, and cultural practices. For example, winter lake ice facilitates access to hunting and fishing grounds (Knoll et al., 2019), supports transportation corridors such as ice roads used by remote communities (Barrette et al., 2022; Ford et al., 2023), and sustains recreational, cultural, and spiritual practices that rely on seasonal ice conditions (Knoll et al., 2019; Magnuson & Lathrop, 2014). As these activities depend on the presence of sufficiently thick and stable ice, changes in lake ice conditions can have significant implications for safety, livelihoods, and community traditions.

Anthropogenic climate warming is rapidly altering lake-ice regimes across the northern hemisphere (Magnuson et al., 2000; Sharma et al., 2019). Observational records show that many lakes now freeze later in autumn, break up earlier in spring, and experience shorter periods of ice cover than in previous decades (Benson et al., 2012; Magnuson et al., 2000; Newton & Mullan, 2021; Sharma et al., 2021). Concurrently, reductions in ice thickness and changes in ice composition are increasing safety risks for individuals and communities that depend on winter lake travel and recreation (Culpepper et al., 2024; Woolway et al., 2022). These changes are projected to affect lake ecosystems by modifying the duration and characteristics of winter conditions, altering habitat availability, and shifting the seasonal progression of physical and biological processes (Cavaliere et al., 2021; Hampton et al., 2017; Jansen et al., 2021). As a result, lake ice functions as a key regulator of freshwater systems and a sensitive indicator of ongoing climate change with direct societal consequences.

Assessing the ecological and societal impacts of changing lake ice involves examining two main aspects: ice phenology and ice quality. Ice phenology refers to the timing of freeze-up (ice-on) and break-up (ice-off), reflecting the duration of seasonal ice cover on lakes (Livingstone et al., 2010). In contrast, ice quality describes the internal structure and composition of the ice sheet itself, including the relative proportions and thickness of black and white ice (Weyhenmeyer et al., 2022). These characteristics strongly influence the mechanical strength of ice, which determines its load-bearing capacity, and the opacity of ice, which regulates light penetration to the water column (Culpepper et al., 2024). Together, ice phenology and ice quality determine the ecological conditions beneath the ice and the safety of frozen lakes for human use.

Understanding how lake ice will change in the future requires projecting ice phenology and ice quality across different climate scenarios. Global projections of lake ice conditions are essential for understanding how anthropogenic climate change may affect freshwater ecosystems and the human communities that rely on them. Such projections also provide an important scientific foundation for evaluating potential climate mitigation and adaptation strategies. However, while global projections are useful for illustrating large-scale patterns and long-term risks, they often provide limited insight for regionally or locally actionable strategies (Frame et al., 2018; O'Neill et al., 2020). Bridging this gap requires integrating large-scale climate

projections with practical regional and local interventions, providing a clear cross-scale direction and rationale for policies to address climate change.

In this thesis, I address these challenges by quantifying changes in lake ice phenology and quality across multiple spatial scales. Specifically, I examine historical changes in lake ice conditions across the Northern Hemisphere, identify climatic and environmental drivers that influence these changes, and project future lake ice responses under a range of climate scenarios. Using long-term observational datasets in combination with statistical and machine-learning approaches, this work aims to (1) characterize historical trends in lake ice, (2) identify key climatic and lake-specific drivers, and (3) project future conditions under shared socioeconomic pathway (SSP) climate scenarios. In addition, I evaluate how land-cover patterns and human activities surrounding lakes are linked to ice phenology at regional and local scales, providing insight into potential management strategies to help mitigate ice loss in vulnerable systems.

More specifically, in the second chapter, I analyzed *in situ* ice phenology records from 2,499 lakes across 15 countries, each with an average of 30 years of observations. This chapter assesses historical changes in ice-on, ice-off, and ice duration, and develops predictive models that integrate meteorological variables and lake morphological characteristics to project future ice phenology under Shared Socioeconomic Pathway (SSP) climate scenarios. This chapter addresses the following questions: i) How has ice phenology changed historically? ii) Which climatic and lake morphological characteristics are important for predicting ice phenology? iii) What are the projected changes to ice phenology by 2099 under a suite of SSP climate change scenarios?

In the third chapter, I analyzed 23,613 *in situ* ice-quality records, including black-ice and white-ice thicknesses, collected from 140 lakes across 11 countries. These data were used to build machine learning models that incorporate meteorological, lake morphological, and land cover variables, and to project ice quality and associated load-bearing capacity for 1.12 million ice-covered lakes across the Northern Hemisphere under SSP climate scenarios. This chapter addresses the following questions: 1) How is lake ice quality forecast to change under varying Shared Socioeconomic Pathways (SSP) climate scenarios? and 2) Which regions of the Northern Hemisphere will be able to support traditional ice- dependent human activities in the future, and will hazards associated with those activities increase?

In the fourth chapter, I examined *in situ* ice phenology records from 3,123 lakes, each with an average of 16 years of data, across five eastern U.S. states: Minnesota, Wisconsin, New York, Maine, and Michigan. This chapter investigates how surrounding landscapes characteristics influence lake ice dynamics at both regional and local scales. In particular, I evaluate the potential role of land cover in mitigating changes in ice phenology. This chapter addresses the following questions: 1) Do trends in ice-on and ice-off date differ by landscape type? and 2) What is the relative influence of local land cover, meteorological, and lake morphological factors on ice cover duration? Together, this thesis provides a comprehensive analysis of the future of lake ice, highlights the relationship between projected changes in lake ice and societal development, identifies the need for global-scale actions, and underscores the scope of regional and local approaches to preventing the adverse effects of lake ice loss.

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Chapter 2: Phenological Shifts in Lake Ice Cover Across the Northern Hemisphere: A Glimpse Into the Past, Present, and the Future of Lake Ice Phenology

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Author's Contributions

AB and SS conceived the research ideas and designed the study. AB developed the methodology, conducted the investigation, performed validation and formal analyses, curated the data (with support from KB), and produced the visualizations. AB and SS contributed resources. SS provided supervision, managed project administration, and secured funding. AB prepared the initial draft, and JC made substantial contributions to manuscript refinement, interpretation of results, and subsequent writing. AB, SS, JC, and KB participated in review and editing. All authors contributed to successive drafts and approved the final manuscript for publication.

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Summary

Long-term ice phenology records quantify the effects of climate change on Northern Hemisphere lakes. This study uses lake ice phenological records across a gradient of lake sizes (0.1 to 31,967.8 km^2 in lake surface area) obtained from community science networks. We compiled *in situ* ice phenological records for 2,499 lakes across 15 countries for an average of 30 years. These data revealed that for the last 50 years (1971-2020), the annual mean duration of lake ice cover decreased at a rate of 9 days per decade, with a regime shift in lake ice phenology in the late 1980s. We projected that at the end of the century (2070-2099), ice duration will decrease by an average of 10 days when compared to the historical time period (1971-2000) for the Shared Socioeconomic Pathway (SSP) 1-2.6 climate scenario (SSP126), 23 days for SSP370, and 28 days for the SSP585. Impending human development can enhance or attenuate lake ice loss, as adaptation strategies can accelerate fossil fuel use, result in conflict, or seek strategies apart from fossil fuel development. These future pathways have critical implications for the future preservation of lake ice cover.

Introduction

Future phenological shifts in lake ice will alter physical lake states and ecosystem resilience (Hansen et al., 2022; Woolway, Sharma, et al., 2022), in addition to altering the cultural relationships with lake ice cover (Knoll et al., 2019; Magnuson & Lathrop, 2014) and ice safety (Sharma, Blagrave, et al., 2020). Lakes have been losing ice cover since the Industrial Revolution (Benson et al., 2012; Magnuson et al., 2000; Sharma et al., 2016). These rates of ice loss have accelerated in the last 25 years compared to the last 150 years (Imrit & Sharma, 2021; Sharma, Blagrave, et al., 2021). By the end of the century, climate warming may result in lakes losing a projected 28–80 days of ice cover (Grant et al., 2021), experiencing intermittent ice cover (Sharma et al., 2019), experiencing multiple freeze-thaw events within a winter season (Sharma, Richardson, et al., 2021), or permanently losing ice (Sharma, Blagrave, et al., 2021) unless aggressive climate mitigation occurs in the immediate future (IPCC, 2022).

Modeling and predicting the future behavior of lake ice phenology remains a critical goal of winter limnology to quantify the impacts of winter ice loss on the people and ecosystems that rely on ice cover. Ice formation in lake models is primarily forced by the same known first-order drivers (L. C. Brown & Duguay, 2010; Sharma, Meyer, et al., 2020), with air temperature as the primary physical variable determining ice timing (Dibike et al., 2011; Palecki & Barry, 1986; Vavrus et al., 1996). Other important meteorological and climate-related factors include precipitation, cloud cover, solar radiation, and wind speed (L. C. Brown & Duguay, 2010; Kirillin et al., 2012). However, local-scale lake morphological factors mediate the impact of regional and large-scale climate drivers. These factors include lake depth, volume, surface area, shoreline length, watershed characteristics, and elevation (L. C. Brown & Duguay, 2010; Sharma, Meyer, et al., 2020).

Global lake ice phenology projecting studies have predominantly relied on physical-based modeling and simulation approaches (i.e., Grant et al., 2021; Huang et al., 2022; Wang et al., 2022). Modeling work relies on simplified lake systems, often homogenizing lake morphology (Dibike et al., 2011; Samuelsson et al., 2010). For example, global circulation models that incorporate lake ice parameters often assume a mean lake depth and lake-area fraction for each grid cell, which results in a useful global summary of lake ice phenology but ignores the real-life variability and heterogeneity of lakes within a grid (Grant et al., 2021;

Huang et al., 2022; Woolway, Huang, et al., 2022). Therefore, discrepancies appear when comparing a global model to a regional model. For example, modeling using the Community Earth System Model version 2 large ensemble (CESM2-LE) projects a global average decrease of approximately 0.48 days per year between 2020 and 2100 (Huang et al., 2022). Meanwhile, projections for lakes in the Tibetan Plateau show an average duration decline of 0.25 days per year (Ruan et al., 2020).

An over-representation of larger lakes may additionally skew ice phenology results, particularly since lakes smaller than 1 km^2 are the most numerous lakes (Verpoorter et al., 2014) and are often excluded from remote sensing, modeling, and simulation studies. For example, a lake ice model driven by satellite imagery requires lakes to be large enough to be resolved by 4 km grid cells, which is larger than most lakes (L. C. Brown & Duguay, 2012), although it is now possible to resolve lake ice phenology on lakes with surface areas as small as 1 km^2 using remote sensing (X. Yang et al., 2022). To date, models that aim to understand small lakes may only examine a single lake for future projections (Tan et al., 2018), but upscaling to understand the behavior of a gradient of lake sizes is critical to understanding ecosystem processes driven by temperature warming (Adrian et al., 2009; O'Reilly et al., 2015; Tan et al., 2018). Therefore, a global-scale model that incorporates a gradient of lake sizes will offer further insights into the behavior of lake ice phenology and duration under different projected warming scenarios, which can only occur through the aggregation of long-term, direct human observations of ice records.

In this study, we ask: i) How has ice phenology (timing of ice-on and ice-off) changed historically?; ii) What climatic and lake morphological characteristics are important for predicting ice phenology?, and iii) What are the projected future changes to ice phenology by 2099 under a suite of SSP climate change scenarios? We use *in situ* observations from 1,947 lakes with ice-on dates and 2,447 lakes with ice-off dates to train and validate ice-on and ice-off models and subsequently to project lake ice loss for 1.12 million lakes across the Northern Hemisphere by the end of the century. We use the Shared Socioeconomic Pathways (SSP) climate scenarios for future projections since they are developed by integrating climate model projections, distinct socioeconomic realities, and assumptions about climate policies (O'Neill et al., 2014, 2020).

To our knowledge, this study uses the most comprehensive ice phenology dataset directly collected through human observation over the past several decades to predict future ice phenology for lakes across the Northern Hemisphere. Thirty-nine percent of the lakes in our database are small lakes (surface area ≤ 1 km^2). To our knowledge, this is the first study to project ice phenology across the Northern Hemisphere with extensive *in situ* observations (rather than simulated data) and includes small lakes, which are the most numerous worldwide (Verpoorter et al., 2014). Notably, these predictions use Shared Socioeconomic Pathways climate scenarios, closely linked to human societal development choices and the establishment of global policy.

Methods

1. Data Acquisition

For this study, we collated i) community science *in situ* observations of lake ice-on and ice-off dates, ii) lake morphological data from HydroLAKES (Messager et al., 2016) and GLOBathy (Khazaei et al., 2022), and iii) historical and future projections of meteorological data (Harris et al., 2020; "ISIMIP3b bias-adjusted atmospheric climate input data," 2021).

1.1. Ice Phenology

The ice phenology dataset consists of 2,499 lakes from 15 countries, with collection periods ranging between 1 - 579 years (Figure 1, supplementary Figure S1). The sources of ice phenology data include direct human observations that have been summarized in the National Snow and Ice Data Center (NSIDC), Lake Ice Analysis Group (LIAG) (Benson et al., 2000); Minnesota Department of Natural Resources (MNDNR); Community Lake Ice Collaboration (CLIC) Project (www.lakeicefreeze.com); and data collected by collaborators from across the Northern Hemisphere (Sharma et al., 2022). The ice-on and ice-off date definitions remained consistent over the years for each individual lake but may differ between lakes (Sharma et al., 2022). Though this dataset represents one of the most comprehensive *in situ* datasets on Northern Hemisphere ice phenology, a preponderance of the data comes from North America, which is likely to skew *in situ* data analyses toward a North American bias.

To address the climate and morphological drivers of ice phenology, we imputed missing phenology data using the following criteria: 1. If the freezing status of a lake for a specific year

is unknown or if the lake froze but the date was not recorded, we imputed the phenology data with the average of the entire ice phenology time series for that lake. 2. When a lake did not freeze, we imputed the ice-on and ice-off values with the latest freezing and earliest thawing dates respectively from the entire record of that lake. 3. The above imputations were done (i.e., criteria 1. and 2.) only if ≥ 20 years of data exist for the lake (sensu Sharma, Blagrave, et al., 2021). Based on these three criteria, we imputed only 0.08% of ice-on data and 0.04% of ice-off data. We imputed data solely for model development to project future ice phenology, but we did not impute data to analyze historical ice phenology patterns. Therefore, the imputed data did not impact trend results for ice-on and ice-off timing.

1.2. Lake Morphology

For lake morphological characteristics, we extracted the following variables from the HydroLAKES database: lake area (square kilometers), shoreline length (kilometers), shoreline development (unitless ratio of shoreline length and circumference of a circle with the lake's area), total volume (million cubic meters), average depth (meters), elevation (meters above sea level), and watershed area (square kilometers) (Messager et al., 2016). The HydroLAKES model estimates the lake bathymetry from the land surface topography surrounding the lake. The HydroLAKES database accounts for all lakes with a surface area greater than 0.1 km^2 (Messager et al., 2016). Additionally, we extracted each lake's maximum depth (meters) from the GLOBathy database (Khazaei et al., 2022). GLOBathy estimates the maximum depth of a lake from the lake's geometric and geophysical characteristics (Khazaei et al., 2022). Supplementary Table S1 summarizes the morphological predictor variables used for building the random forest models.

1.3. Meteorology

Historical meteorological data were obtained from the University of East Anglia's Climatic Research Unit (CRU), supported by the United Kingdom's National Centre for Atmospheric Science (NCAS) (Harris et al., 2020). For each lake, we recorded monthly near-surface (2 meters above the surface) air temperature (degrees Celsius) and precipitation (mm day^{-1}) at a spatial resolution of 0.5 degrees dating back to 1901 from the CRU TS version 4.06 database (Harris et al., 2020). Historical (1971-2000) and future (2015-2099) projections of daily near-surface temperature and precipitation data were obtained from the Inter-Sectoral Impact

Model Intercomparison Project (ISIMIP) 3b simulations ("ISIMIP3b bias-adjusted atmospheric climate input data," 2021). We acquired three combinations of Shared Socioeconomic Pathways (SSPs) and representative concentration pathways (RCPs): SSP1-RCP2.6 (i.e., SSP126), SSP3-RCP7.0 (SSP370), SSP5-RCP8.5 (SSP585) for future ice phenology projections. Only the primary input data used to drive climate impact models were extracted: SSP126, SSP370, and SSP585 ("ISIMIP3b bias-adjusted atmospheric climate input data," 2021).

The SSP585 scenario focuses on the fossil fuel development pathway (SSP585), where human development goals, economic growth, and infrastructure growth are attained through burning fossil fuels (O'Neill et al., 2017). Highly connected global markets, technological advancements, and innovations characterize this scenario with an additional radiative forcing of 8.5 W/m² by 2100. This scenario poses high mitigation challenges (here, mitigation means reducing climate change by limiting the emission of greenhouse gases) due to reliance on fossil fuels, a globally prevalent energy-intensive lifestyle. This scenario also poses low adaptation challenges (here, adaptation means adjusting life according to posed changing climate) due to the existence of life-supporting infrastructure and social security achieved from expending fossil fuel energy (O'Neill et al., 2014, 2017).

The SSP370 scenario is characterized by regional rivalry with an additional radiative forcing of 7.0 W/m² by 2100. This scenario's social characteristics are defined by resurgent nationalism. Nationalism focuses on competitiveness, security, and regional conflicts and leads to greater challenges in developing global climate mitigation due to the absence of global cooperation required to mitigate climate change effectively. Nationalism also poses equally great challenges to adaptation strategies due to limited progress in human development, economy, and effective institutions (O'Neill et al., 2017). The policies are increasingly centered around national and regional security concerns. Investments in education and technological progress decline, and inequality escalates with certain regions experiencing severe environmental harm.

The SSP126 scenario characterizes a sustainable and "green" approach with an additional radiative forcing of 2.6 W/m² by 2100. The SSP126 scenario poses low mitigation and adaptation challenges for society because it emphasizes inclusive development, which respects the environmental boundaries required to preserve the current environment. In this scenario, the advancement of human well-being is prioritized rather than the sole pursuit of economic growth

while a commitment is made to reduce income disparities both globally and within nations. Consumption patterns are designed to limit the use of material resources and energy (O'Neill et al., 2017).

2. Data Analysis

Ice-on and ice-off dates were converted to the day of the year relative to December 31st. The reference date of December 31st was zero. For example, if a lake froze on December 20th, the ice-on day would be -11, whereas if a lake froze on January 10th of the following year, the ice-on day would be +10. For all meteorological data (CRU TS and ISIMIP3b), seasonal means of monthly temperature and precipitation were calculated (JJA is summer, SON is fall, DJF is winter, and MAM is spring). We identified the temperature component of the ice-on model by summing the summer, fall, and winter air temperature averages. Ice-off dates were modeled by summing the winter and spring temperature averages. A similar method was used for precipitation when modeling ice-off dates. In contrast, the sum of only fall and winter precipitation averages was used for modeling ice-on dates.

2.1. How has ice phenology changed over time?

The data points had a negatively skewed distribution, such that ice-on dates go back to 1443 and ice-off dates back to 1757. The 25th percentile of both ice-on (the year 1974) and ice-off (the year 1968) were calculated (supplementary Figure S1) to create a common cut-off date (the year 1971) to reduce the skewness of the data. Although we used all ice phenological data when appropriate, we focused on 50 years of data (1971 to 2020) to estimate changes to ice phenology patterns over time. For this analysis, we first converted a lake's ice-on dates to anomalies relative to the lake's 50-year (1971-2020) mean ice-on date. A global ice-on anomaly time series was then calculated as an average of these ice-on anomalies across all lakes. We applied a similar procedure to ice-off dates. The lakes used for ice-on (1,899 lakes), and ice-off anomaly (2,397 lakes) calculations are shown in supplementary Figure S3. We identified breakpoints (change points in the mean) in the 50-year average ice-on and ice-off anomaly time series data using the R package "strucchange" (Zeileis et al., 2003). In this analysis, the optimal number of significant breakpoints for each of the ice-on and ice-off anomaly time series was identified. We used the Quandt Likelihood Ratio statistic over the first-order autoregression model to identify breakpoints and numbers of optimal segments with a condition that 15% of the

total time-series data is required to have a segment. The Chaw test was performed to obtain the p-value, and we plotted F-statistics values against time with a line denoting an alpha value of 0.05 (supplementary Figure S2). We also calculated a mean ice duration for every year over the period 1971-2020 from the set of lakes that have both ice-on and ice-off dates. We performed a Mann-Kendall test on mean ice duration to check if a significant monotonic trend exists. We then used a Sen's slope analysis to quantify a significant trend. A breakpoint analysis was also carried out on mean duration, and one optimal breakpoint was observed for the year 1988 (supplementary Figure S4). These data are the most extensive available; however, data are highly concentrated in North America. The concentration of data in North America compared to other parts of the world (Figure 1) likely skews both overall trends and breakpoints. Therefore, we also examined trends and breakpoints regionally in Europe and North America (supplementary Figure S5, Text Box S1).

2.2. How well do random forest models predict ice phenology?

We compared various machine learning approaches to select the best-performing model to predict future ice phenology and ice cover duration. To train, validate, and test the models, we used all of the *in situ* data available in our database, which have corresponding meteorological data. Hence, we used 37,369 observations from 1,947 lakes for the ice-on model and 46,863 observations from 2,447 lakes for the ice-off model, both spanning from 1901-2019. We initially tested models using ridge, lasso, elastic-net regression, k-nearest neighbors, random forest, decision tree, support vector machine, and artificial neural network regression (refer to supplementary section 1.2 for more details). As the random forest was the most parsimonious model among all tested, we selected the random forest for training and validating future projection models and will be the focus for the remainder of the study.

We created a test set that was spatially and temporally independent from the training and cross-validation to characterize model performance. To spatially group the data, we used the "BlockCV" R package (Valavi et al., 2019) to create randomly generated hexagonal spatial blocks with ten subsets of data or "folds", where each block is 250 km in width. After assigning the spatial blocks, the lakes are randomized and rearranged from oldest to most recent observations so that the same lake time-series are not grouped together. This arrangement is divided into 10 equal groups (time-folds) and cross-validated by the "leave-location-and-time-

out" resampling method. We implemented random spatiotemporal splits, where from each group combination, 80% of the data were used for training and 20% for testing the model. The 10-fold spatiotemporal cross-validation was implemented using "mlr3spatiotempcv" (Schratz & Becker, 2024). We trained the random forest model using the "ranger" R package (Wright & Ziegler, 2017) in conjunction with the "mlr3verse" (Lang & Schratz, 2023) package for hyperparameter tuning. The hyperparameter values for ice-on, ice-off, and freeze/no-freeze models are denoted in supplementary Text box S2.

We used root mean square error (RMSE), mean absolute error (MAE), R-Square, and slope of the fitted line between predicted and observed data from the testing set as evaluation matrices for assessing model performance (supplementary Figure S6a). Symmetric mean absolute percentage error (SMAPE) for each lake from predicted and true values were calculated from the testing dataset to identify the spatial dependency of model performance (supplementary Figure S6b).

2.3. What are the most important meteorological and lake morphological drivers of lake ice phenology?

We used air temperature, precipitation, lake area, shoreline length, shoreline development, total volume, average and maximum depth, elevation, and watershed area to predict ice-on and ice-off dates. Based on the random forest models, we measured the importance of each variable influencing ice-on and ice-off dates. The distribution of minimal (tree) depth and its mean was observed for all the variables using the R package "randomForestExplainer" (Paluszynska et al., 2020). The minimal depth for a variable in a tree is measured as the depth of the variable splitting node closest to the root of the tree, which means the higher the importance of the variable, the lower the minimal depth. The effects of lake morphology on ice-on and ice-off dates were further analyzed and interpreted by using partial dependence plots through the "DALEX" (Biecek, 2018) and "DALEXtra" package (Maksymiuk et al., 2020) for the ice-on and ice-off random forest model. The variable importance of the classification random forest model (freeze/no-freeze) was also analyzed by investigating the distribution of minimal depth and its mean for all variables. The confusion matrix for the classification model was added to the supplementary section (Figure S7). The temperature and precipitation amounts for both ice-on and ice-off models (as denoted in section 2.2) are used,

along with the morphological variables lake area, shoreline development, total volume, average and maximum depth, and elevation to build this classification model.

2.4. What are the projected changes in ice phenology by the end of the century?

We used the most parsimonious models for both ice-on and ice-off events (random forest models, Section 3.2), coupled with climate projections from the suite of Shared Socioeconomic Pathways (SSP), to project future changes to ice phenology. We extrapolated our most parsimonious models until the end of the century for the Northern Hemisphere lakes ≥ 0.1 km^2 (Messager et al., 2016) with average winter temperatures ＜–0.4 °C (Sharma et al., 2019; Weyhenmeyer et al., 2004) and situated below 70°N Latitude. A limit of 70°N latitude was used, as the training data are scarce above 70°N (supplementary Figure S8).

The model was suitable for understanding shifts in phenology patterns in days but not suitable for predicting lake ice occurrence, as the no-freeze years for a particular lake were imputed using the latest freezing and earliest thawing dates of the lake's time series (as described in section 2.1.1). Hence, a random forest classification model was also built to assess whether a lake will freeze or not in future years with the same explanatory variables used for the prediction of ice-on and ice-off dates. To improve the representation of ice cover duration for each lake, we merged the ice-on, ice-off, and classification models. Initially, the duration was calculated from differences in ice-off and ice-on day of the year. We replaced this duration with zero for years when the classification model suggested a no-freeze event.

We then used observations of ice occurrence to classify lakes as seasonally frozen, intermittently frozen, or not reliably frozen. Seasonally frozen lakes continue to freeze each winter throughout the end of the century. Lakes we classified as no longer reliably freezing experience 50% or more years without a freezing event over a 30-year historical (1971-2000) period/ future (2070-2099) period. Intermittently frozen lakes included lakes that have at least one year when they do not freeze within the 30-year window. We used 1,484 lakes with a total of 49,002 records to train and test the data 10-fold spatiotemporal cross-validation, with 80% of the data as the training set and 20% as the testing set.

Finally, we calculated the variability in ice phenology for each of the 1.12 million lakes for every SSP scenario studied. The variability in the timing of ice-on and ice-off for each lake

was represented by the standard deviation of ice-on dates, ice-off dates, and/or duration, each within an 85-year window (2015-2099). We compared all three future SSP scenarios (all data points of 1.12 million lakes over the period 2070-2099) with the historical ice-on and ice-off dates (all data points of 1.12 million lakes over the period 1971-2000). A schematic diagram summarizing all of the analysis is depicted in Figure 2.

Results

1. How has ice phenology changed over time?

Ice-on dates were later and ice-off dates were earlier over the past 50 years (1971-2020). (Figure 3 a,b). A significant (< 0.001) Mann-Kendall test was obtained showing that a monotonic trend exists for mean ice duration change. Furthermore, from Sen's slope analysis, the mean annual lake ice duration was observed to decrease at a mean rate of 9 days per decade over the last 50 years (1971-2020) (Figure 3c). A caveat to the analysis is that *in situ* data primarily derives from North America. When separating the data between North America and Europe and Asia, it is evident that the signal primarily derives from North America with some additional variation likely added from Europe and, to a lesser extent, Asia (supplementary Figure S5b,c). However, the limitations on *in situ* data required us to use all available data for a more robust modeling effort.

The change point detection analysis identified an ice-on breakpoint in 1989 (p-value < 0.001) and an ice-off breakpoint in 1988 (p-value < 0.001) (Figure 3 d, e). At the breakpoint, on average, the ice-on anomalies shifted to later ice-on average dates compared to the 50-year mean. The average ice-on anomaly for 1,899 lakes prior to 1989 was 7.8 days earlier than the 1971-2020 average. After the 1989 breakpoint, the average ice-on anomaly date was 1.7 days later. Conversely, the ice-off anomalies shifted to an earlier ice-off average date after 1988, compared to the 50-year mean. The ice-off anomaly for the 2,397 lakes was an average of 11.5 days later before the 1988 breakpoint but became 2.8 days earlier after 1988. For mean duration change, one optimal and statistically significant (p-value < 0.001) breakpoint was observed for the year 1988 (supplementary Figure S4), capturing the increased variability observed around and after 1990 in ice cover duration (Figure 3c).

2. How well do random forest models predict ice phenology?

The random forest model, generated from 1901-2019 (118 years), predicts ice formation and breakup with a good overall model fit, where the ice-off model performed significantly better than the ice-on model. The ice-on random forest model had a mean absolute error (MAE) of 8.49 days, a root mean square error (RMSE) of 11.66 days, and an R-squared value of 0.72. The ice-on model intercept was 0.46 and had a slope value of 1 (supplementary Figure S6a, Table S3). The ice-off model has a MAE of 6.4 days, a RMSE of 8.87 days, and an R-squared of 0.85. The intercept and slope values for the ice-off model were -1.4 and 1, respectively (supplementary Figure S6a, Table S3). A confusion matrix for the classification model was generated (supplementary Figure S7). In summary, the classification random forest model on the testing dataset produced F1 scores of 0.9960 for the freeze class, 0.7778 for the no-freeze class, and a weighted F1 Score of 0.9925 (99.25%). Symmetric mean absolute percentage error (SMAPE) was highest at 2% for the ice-on model and 1.2% for the ice-off model. Overall, for ice-on, lower latitude lakes (40 - 45°N) and coastal areas in Alaska and Europe have a higher error (supplementary Figure S6b). Overall, the ice-off model produced lower symmetric mean absolute percentage error than the ice-on model in terms of overall spatial spread.

3. What are the important meteorological and lake morphological characteristics influencing ice phenology?

We observed that air temperature and precipitation were the two most important variables for ice-on. Meteorological variables had the lowest mean tree depth (i.e., more commonly split the data near the root node), which improved model performance (Figure 4a). The difference in mean tree depth between precipitation (1.69) and temperature (1.7) was negligible, while the difference between the meteorological variables and the lake morphological variable with the lowest mean tree depth (1.94) was distinct. The similar importance of both air temperature and precipitation may be caused by the influence of air temperature on precipitation, where air temperatures at or above 0 °C result in precipitation as rain, which can mix and warm a lake. For ice-off, air temperature, lake mean depth, and elevation were the most important variables (Figure 4b). Ice-off temperature was more important (1.12 mean tree depth) than the following two lesser but similarly important morphological variables: mean lake depth (1.71 mean tree depth) and elevation (1.78 mean tree depth). Ice-on partial dependence plots (Figure 4c top row) illustrated that ice-on occurs later with increasing precipitation, warmer temperatures, and for

deeper lakes. Similarly, for ice-off, partial dependence plots revealed that ice-off dates were earlier in regions with warmer temperatures and lower elevation and for shallower lakes (Figure 4c bottom row). Further, the classification random forest model (freeze/no-freeze) variable importance plot (Figure 4d) illustrates that air temperatures during ice-off, air temperatures during ice-on (see section 2.2.), elevation, maximum lake depth, and precipitation during ice-off (see section 2.2.) were the top five most important variables for predicting whether a lake will freeze or not.

4. What are the projected future changes in ice phenology by 2100 under a suite of climate change scenarios?

Under future warming scenarios, our random forest model projected progressively earlier ice-on and later ice-off dates for Northern Hemisphere lakes when using more pessimistic SSPs. Ice-on is projected to be, on average, 4 ± 15 days later by 2099 for the SSP126, 10 ± 16 days later for SSP370, and 12 ± 16 days later for SSP585, when comparing values over the period 1971-2000 and 2070-2099. Ice-off dates were projected on average to be 6 ± 19 days earlier for SSP126, 12 ± 20 days earlier for SSP370, and 15 ± 20 days earlier for SSP585. This pattern of progressive increase in ice loss from warmer scenarios was observed for projected historical (1971-2015) and to different degrees for the three future (2016-2099) SSP scenarios (Figure 5) for 1.12 million lakes. Therefore, these lakes were projected to lose, on average, 10 ± 33 days of ice cover within the SSP126 scenario, 23 ± 35 days for SSP370, and 28 ± 36 days for the SSP585 scenario by the end of the century. The observed large standard deviation values (33-36 days for ice cover duration and 15-20 days for ice-on or ice-off days) occurred primarily because of regional variability present in lake ice phenology (e.g., northern lakes naturally freeze for a longer duration every year than southern lakes).

The relative change between historical (1971-2000) and future (2070-2099) averages of ice cover duration was markedly higher between SSP126 and the two other warming scenarios throughout the Northern Hemisphere (Figure 6). While relative change is more evenly distributed over the Northern Hemisphere, lower latitude and coastal lakes are most vulnerable to losing ice cover in absolute terms (supplementary Figure S9). Lake ice cover was most preserved within the SSP126 scenario, compared to the SSP370 and SSP585 scenarios (Figure 6, S9). A Sankey plot was created to explore relative changes in durations observed from historical to

progressively warmer SSP scenarios (Figure 7). For example, in the SSP126 scenario, 45% of lakes were projected to lose 10 days or less of ice cover. Under the SSP375 scenarios, only 1.78% of lakes were projected to lose less than 10 days of ice cover and this percentage declined to 0.91% for the SSP585 scenario (Figure 7). More explicitly, for the SSP585 scenario, this implies that only 0.98% of lakes will experience 10 days or less of ice loss, whereas the remaining lakes will experience more than 10 days of loss in ice cover duration. Likewise, the random forest classification model was used to classify lakes within the projections that will continue to freeze, freeze intermittently, or not reliably freeze for all the historical (1971-2000) and future (2070-2099) SSP scenarios (supplementary Figure S10). The variation in ice phenology changes for different lakes is visualized in Figure 8. Moreover, the variability in ice phenology dates for lakes increased in the higher emission scenarios, although not latitudinally (supplementary Figure S11).

Discussion

The seasonal cycle of open water and ice cover has been a regular occurrence for freshwater lakes across much of the Northern Hemisphere (Filazzola et al., 2020; Walsh et al., 1998), but is threatened by climate warming (Sharma et al., 2019). The formation of lake ice depends on a sufficient gradient of temperature such that lake water ejects heat into the atmosphere, freezing after a prolonged period of air temperatures at or below 0 °C (Blagrave & Sharma, 2023; L. C. Brown & Duguay, 2010). This cycle and the various ecosystem services provided by winter ice cover have been taken as a seasonal certainty for many Northern Hemisphere lakes. However, this regular cycle is threatened to be disrupted as air temperatures warm with climate change (Li et al., 2022). The timing of ice-on and ice-off is affected by shifts in the traditional timing of seasons, reducing the length of the ice-cover season. In extreme cases, the length of this season has even been reduced to zero days in some years as lakes shift from perennially freezing to intermittently freezing to no longer reliably freezing (Filazzola et al., 2020; Sharma, Blagrave, et al., 2021). The effect of air temperature on ice phenology is not homogeneous across all lakes. Lake morphometry influences how the radiative heat input at the surface is subsequently distributed across the lake (L. C. Brown & Duguay, 2010). Likewise, lake morphometry will influence how long it takes for the lake to lose its store of heat to the atmosphere in the fall, thus influencing the timing of ice formation. Once ice initially forms,

morphometry may again play a role via the fetch. If there is sufficient wind, this initial skim ice may break up; thus, lakes with a larger fetch may form ice later in the season than other lakes in the region (Adams, 1976; L. C. Brown & Duguay, 2010; Magee & Wu, 2017; G. Williams et al., 2004). At the end of the ice season, morphometry plays less of a role, with little correlation between ice-off and surface area or depth (Blagrave & Sharma, 2023; Shuter et al., 2013). However, small lakes may still experience earlier ice-off than large lakes. An increase in air temperature increases the effect of lateral ice loss (Arp et al., 2013), and the relative importance of this ice loss as compared to the overall ice loss is generally greater in smaller lakes (Arp et al., 2013; Nõges & Nõges, 2014).

Many additional factors influence the timing of ice-on and ice-off. Mechanistic models use a variety of meteorological, hydrological, and lake morphometry inputs to calculate the flux of heat into and out of a single lake system, determining seasonal stratification, initial ice formation, ice growth and decay, and ice break-up (i.e., Bueche et al., 2017; Kirillin et al., 2012; Leppäranta, 2009; Yao et al., 2014). Likewise, empirical models have shown that – in addition to lake morphometry and air temperatures – rainfall, snowfall, and solar radiation have varying influences on ice phenology (i.e., Imrit & Sharma, 2021; Magee et al., 2016; Moore et al., 2021). Most prominently, solar radiation plays a significant role in the timing of ice off (Kirillin et al., 2012; Leppäranta et al., 2010). Once snow has melted, the temperature of the water under the ice increases with the absorption of solar radiation, and if air temperatures are also warm enough, ice thickness is reduced, leading to the eventual ice break-up (Kirillin et al., 2012; B. Yang et al., 2017; X. Yang et al., 2020).

1. How has ice phenology changed over time?

We found that over the last 50 years (1971-2020), ice duration decreased at a rate of 9 days per decade on average, which is seven times higher than found in previous studies for lakes that have data between 1971 and 2020 (1.3 days per decade, on average; Benson et al., 2012; Imrit & Sharma, 2021; Lopez et al., 2019; Newton & Mullan, 2021; Sharma, Richardson, et al., 2021). We suspect that our focus on the last 50 years of ice records led to the higher number of days of ice loss (9 days/decade) and higher variability in lake ice loss since 1990 (Figure 3c). There appears to be a regime shift in the late 1980s after which ice duration is lower (supplementary Figure S4). In fact, Sharma, Richardson, et al. (2021) calculated trends of ice

loss on the order of 10.6 days per decade for the 1992-2016 time period, which is six times faster than any other time period in the past 100 years. Additionally, our estimates included a larger number of lakes (n = 2499) and may be capturing additional variability in ice phenology. However, in the longer historical *in situ* records of ice-phenology across the Northern Hemisphere, declines are less pronounced (Benson et al., 2012; Magnuson et al., 2000; Newton & Mullan, 2021; Sharma, Blagrave, et al., 2021). For example, Imrit & Sharma (2021) observed that Northern Hemisphere lakes froze 1.1 days later and thawed 0.9 days earlier per decade by comparing records of 18 lakes with very long records, between 156 and 204 years. Sharma, Richardson, et al. (2021) calculated that, on average, 60 lakes with similarly long records (107-204 years) lost 1.7 days of ice cover per decade. Their study of 678 Northern Hemisphere lakes, (Newton & Mullan, 2021) found that 0.63 days per decade of ice were lost over the period 1931–2005. Benson et al. (2012) demonstrated a similar decrease in ice duration at a rate of 0.86 days per decade over a 150-year period and 0.46 days per decade over a 100-year period over the years 1855-2005 and 1905-2005, respectively, for 75 lakes. Over the period of 1952-2014, ice-off occurred 1.2 days per decade earlier from 152 lake records across the Northern Hemisphere (Lopez et al., 2019).

We found a breakpoint in the 1988-1989 ice season (Figure 3a,b, and supplementary Figure S4) corresponding to natural and anthropogenic-induced global climate shifts in the 1980s (Reid et al., 2016). This regime shift in the 1980s was observed in many biogeophysical systems across the planet (Reid et al., 2016), including the carbon cycle (Beaulieu et al., 2012), fish populations in freshwater ecosystems (Hari et al., 2006), snow cover across Northern Hemisphere (R. D. Brown & Robinson, 2011), precipitation at Tarim river basin (Tao et al., 2016), atmospheric earth system changes (Lo & Hsu, 2010), and lake ice-off patterns (Lopez et al., 2019). Furthermore, the widespread abrupt warming observed across the Northern Hemisphere in the late 1980s may be associated with shifts in the Pacific Decadal Oscillation and Arctic Oscillation (Lo & Hsu, 2010). Hence, the shift observed in this study in ice phenology patterns for both ice-on and ice-off might be a reflection of Northern Hemisphere lakes undergoing a regime shift at the end of the 1980s.

2. How well do random forest models predict ice phenology?

The ice-off model explained 13% more variation than the ice-on model. As anticipated, the discrepancy between the explanatory power of the ice-on and ice-off models arises because the ice-on phenology is more intricate, relying heavily on meteorological and lake morphological variables. Conversely, meteorological factors predominantly drive ice-off phenology (L. C. Brown & Duguay, 2010). Ice-on and ice-off models performed poorer for low-duration ice years, as more variance is observed during those years (supplementary Figure S6a). This pattern was expected as both models cannot practically denote a date representing a no-freeze event. Hence, combining the freeze/no-freeze classification model with duration calculations will combine the strengths of each type of model to improve duration prediction accuracy. Individually, both the ice-on model and ice-off model have shown minimal systematic bias from the slope (>0.01 significant digit) and a small, consistent overestimation bias (intercept of 0.46) for the ice-on model and comparatively larger underestimation bias (intercept of -1.4) for the ice-off model. Overall, the symmetric mean absolute percentage error (SMAPE) for the ice-on model is observed to be higher than the ice-off model, which is expected as the ice-off model performs better than the ice-on model (supplementary Figure S6 a,b). For the ice-on model, lower latitude lakes (40 - 45 °N) and coastal areas in Alaska and Europe have a higher error, indicating a higher chance of bias in those areas. No specific spatial pattern of higher or lower SMAPE was observed for the ice-off model. For both models, the overall error percentage is low. A low SMAPE was expected as 10-fold spatiotemporal cross-validation was applied to train the model, which minimizes spatial and temporal bias. Long-term ice phenology records are abundant but highly concentrated in North America (particularly in the NE United States) and Europe.

Ideally, input data for the model would include a well-distributed swath of lakes across the Northern Hemisphere. However, the concentration of lakes in North America and Europe (Figure 1) can introduce bias by including systems that experience similar climatology or even anthropogenic forcing that we have not included in the model. We have focused on location-agnostic physical variables and have used 10-fold spatiotemporal cross-validation techniques to try to inhibit the lack of diversity of lakes within our sample data. Our model does not incorporate key meteorological variables such as solar radiation and wind. Therefore, its performance may be limited in areas where these factors significantly influence ice phenology, such as in the Tibetan Plateau (M. Wang et al., 2022). Extrapolating beyond the training data is common in machine learning due to the need to predict future changes (Chen et al., 2024) or

address gaps in data (Khazaei et al., 2022; Messager et al., 2016), but this can introduce bias. Despite this possible bias, our study provides valuable insights into overall ice-phenology changes due to the robust representation of small lakes in our training data and the combination of regression and classification models to improve accuracy. These insights are relevant for understanding potential changes based on different societal developments in the near future.

3. What are the most important meteorological and lake morphological drivers of lake ice phenology?

The random forest model that predicted ice-on dates explained over 72% of the variation in an independent test dataset. Of the 10 meteorological and morphological variables used to build the random forest model (listed in section 2.2.3), we observed that air temperatures and precipitation are similarly important for ice on dates, followed by mean lake depth (Figure 4a). The timing of ice-on is most influenced by air temperature (Arp et al., 2013; Assel & Robertson, 1995; L. C. Brown & Duguay, 2010; Magee et al., 2016; Palecki & Barry, 1986). Warmer air temperatures are broadly associated with later ice-on dates. Ice formation requires 0ºC surface water temperatures (Leppäranta, 2009); therefore, a warmer season results in later ice-on, owing to slower heat loss given the correlation between ice-on and fall and winter air temperatures (Assel & Robertson, 1995; Palecki & Barry, 1986). This seasonal temperature has been shown to be a good proxy for the daily temperature conditions, explaining similar variation in ice phenology as does the daily record (Sharma et al., 2013). Higher precipitation levels during the fall and winter seasons were correlated with later ice-on dates (Figure 4c). This additional input into the lake may increase the lake's surface temperature (L. C. Brown & Duguay, 2010). Precipitation may also be associated with storms and, thus, increased wind speeds, which could lead to mixing and turbulence. In both situations, the effect of increased precipitation would most likely be later ice-on dates. Precipitation is connected to warmer temperatures in northern high-latitude environments (Serreze et al., 2000); hence, precipitation and later ice formation can be connected through covariance with warming. An aspect of morphology, such as mean depth, is also highly important in the model. Deeper lakes experienced later ice-on dates (L. C. Brown & Duguay, 2010; Palecki & Barry, 1986; Warne et al., 2020). Removing the heat from these systems takes longer as the entire column of water generally must cool to 4ºC before the onset of inverse stratification and subsequent freezing. The limiting factor for this heat loss is the area of

the water-atmosphere interface. The deeper lake would freeze later for two lakes with the same surface area and experiencing the same climate (Higgins et al., 2021; Nõges & Nõges, 2014).

Air temperature was the most important driver of ice-off dates. In addition, mean lake depth and elevation explained additional amounts of variation (Figure 4b). The random forest model predicting ice-off dates explained 85% of the variation in an independent validation dataset. Higher air temperatures were associated with earlier ice-off, in agreement with a host of other studies that use a variety of methods (e.g., *in situ* data, modeling, and remote sensing) (L. C. Brown & Duguay, 2010; Imrit & Sharma, 2021; Magnuson et al., 2000; Palecki & Barry, 1986; Sharma, Blagrave, et al., 2021; Sharma et al., 2019; Weyhenmeyer et al., 2004; G. P. Williams, 1971). A warmer winter would result in a reduced maximum ice thickness (Arp et al., 2015; Korhonen, 2006; Woolway, Huang, et al., 2022), and ice exposed to elevated air temperatures in the spring increases the rate of ice decay (L. C. Brown & Duguay, 2010). Both result in an earlier ice-off date for warmer seasons.

While lakes at different elevations are exposed to different wind conditions, solar radiation (Palecki & Barry, 1986), and precipitation phase (Jones, 2001), the correlation of lower elevations with earlier ice-off dates is likely associated with warmer temperatures at lower elevations, as was the case for lower elevation lakes and later ice-on dates. Furthermore, according to the model, lakes with deeper mean depths are associated with later ice-off dates (Figure 4c). The variable importance of the ice-off model (Figure 4b) shows that temperature, mean lake depth, and elevation (mean tree depths of 1.12, 1.71, and 1.78, respectively) influence the model. It can be observed that temperature is the root node and depth of 1, which accounts for over half of the trees within the model, indicating that temperature is consistently the most important variable. The lack of a coherently declining node depth for ice-off variables indicates a higher variability for important factors where the random forest model splits individual trees, as seen in the minimum depth plot. Therefore, these variables may covary more than the ice-on model, where the distribution of tree depths and their mean for the ice-on model had a clear gradient. The lower variability of importance for the ice-on model indicates the involvement of those predictor variables (especially temperature, precipitation, average depth, and elevation) in the lake ice-on process.

Our random forest classification model accurately predicted no-freeze seasons (i.e., specificity) 85% of the time and had an F1 score of 0.78 for the no-freeze class. The variable importance plot illustrates that winter and spring air temperatures are the most important predictor of ice freeze/no-freeze status, followed by elevation, maximum lake depth, and ice-on (summer, fall, and winter) air temperatures (Figure 4d). Earlier studies have also suggested the importance of air temperature in ice occurrence models where warmer average air temperatures will lead to intermittent or unreliable freezing of lake ice (Sharma et al., 2019). As elevation predominantly influences air temperature and maximum depth influences lake heat retention capacity, these variables are also important predictors of ice occurrence and intermittent ice cover (Sharma et al., 2019).

4. What are the projected future changes in ice phenology by 2100 under a suite of climate change scenarios?

We project that by the end of the century, 1.12 million lakes will lose, on average, 10 ± 33 days of ice cover for the SSP126 scenario when comparing future (2070-2099) and historical (1971-2000) time periods. Over the same time, lakes are projected to lose an average of 23 ± 35 days for SSP370 and 28 ± 36 days for the SSP585 scenario. Other studies have also projected that lakes are to lose an additional 28–80 days of ice cover (Grant et al., 2021; Huang et al., 2022; X. Wang et al., 2022), experience intermittent winter ice cover (Sharma et al., 2019), or permanently lose ice (Sharma, Blagrave, et al., 2021) by the end of the century. For example, Sharma et al. (2019) predicted that within a 2°C warming scenario, 2.8% of lakes could experience intermittent ice cover (i.e., no longer freezing annually). Furthermore, 5,679 Northern Hemisphere lakes might lose ice cover by the end of the century (Sharma, Blagrave, et al., 2021).

Modeling studies predicting lake ice phenology, such as Huang et al. (2022), projected that ice duration loss would be 38 ± 11 days for the SSP370 pathway at the end of the century. Similarly, Wang et al. (2022) projected an ice loss of 49.9 days by the end of the 21st century under an RCP 8.5 warming scenario. Our results indicate less ice loss when compared to projections from Huang et al. (2022) and Wang et al. (2022). We suggest the difference is due to our study's inclusion of greater numbers of lakes smaller than 1 km^2, which are more likely to freeze longer than larger lakes experiencing similar climatic forcing. The inclusion of smaller

lakes and direct *in situ* measurements in our models are suggesting less ice loss compared to the models predominantly built and tuned on data from larger lakes, either those using remote sensing observations or simulations based on hypothetical lake depths and sizes. Moreover, we observed a much higher variability in ice phenology dates compared to Wang et al. (2022) as variability peaks with shorter ice duration evident by a gradient of lake types, including smaller or higher elevation lakes (Richardson et al., 2024). We highlight the need for including more data directly collected by human observation and a gradient of lake types for future climate projection studies.

When comparing greenhouse gas emission scenarios, we found that the variability of ice-on and ice-off dates increases for higher emission scenarios (supplementary Figure S11). Since the late 1980s regime shift observed in our study, ice duration has become more variable (Figure 3c). Future warmer climate scenarios resulted in higher variability of ice duration (supplementary Figure S11). Weyhenmeyer et al. (2011) observed that within a group of water bodies, the lakes or rivers that freeze later and thaw earlier, experience the highest interannual variability and postulated that variability in ice phenology will increase with climate temperature rising. Thus, the chance of predicting and preparing for adaptation across the Northern Hemisphere will be much more challenging in a future that follows the path predicted by warmer climate scenarios (SSP370 and SSP585). Change in variance is clearly observed in future (2070-2099) ice-on dates when compared to historical (1971-2000) ice-on dates, while this change does not appear to be as prominent for ice-off dates (Figure 9b). We found that ice-on will become much more unpredictable than ice-off dates as ice-on dates experience a greater change in their distribution shape (variance) than the distribution for ice-off dates (Figure 9a).

Projected changes to ice phenology, using the SSP585 scenario, are the most drastic; however, societal and ecological resilience to climate change may be more difficult to achieve when considering the SSP370 scenario. The SSP370 scenario is characterized by regional rivalry defined by resurgent nationalism focusing on competitiveness and regional conflict. The lack of global cooperation will pose challenges to adaptation strategies and rampant inequality of severe environmental harm (O'Neill et al., 2017). Thus, SSP370 poses higher mitigation and adaptation challenges compared to the SSP585 scenario. The most optimistic scenario, SSP126, aims to mitigate climate warming, which may attenuate the rate of ice loss and

reduce the variability of ice phenological timing. As SSP126 poses low adaptation challenges, our global society will likely be better equipped to fight climate change by the end of the 21st century. Hence, our results indicate that the "green" development pathway is preferable to preserve annual lake ice cover. Technological advancements, promotion of human well-being, reducing inequalities, and increased global cooperation to the climate crisis will be essential to mitigate greenhouse gas emissions and preserve our cryosphere.

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Tables and Figures

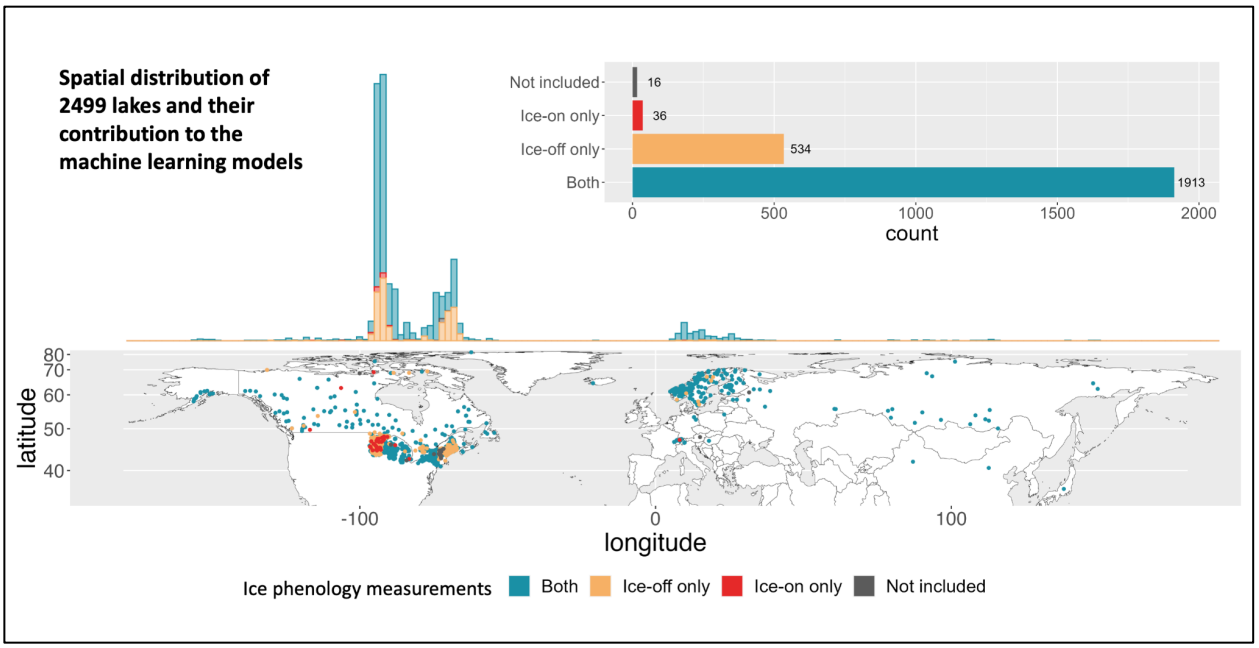


Figure 1: Distribution of ice phenology data, consisting of 2,499 lakes over 15 countries. The upper right corner panel depicts the total number of lakes contributing to ice-on and ice-off dates (both), only ice-on, only ice-off, and lakes not included

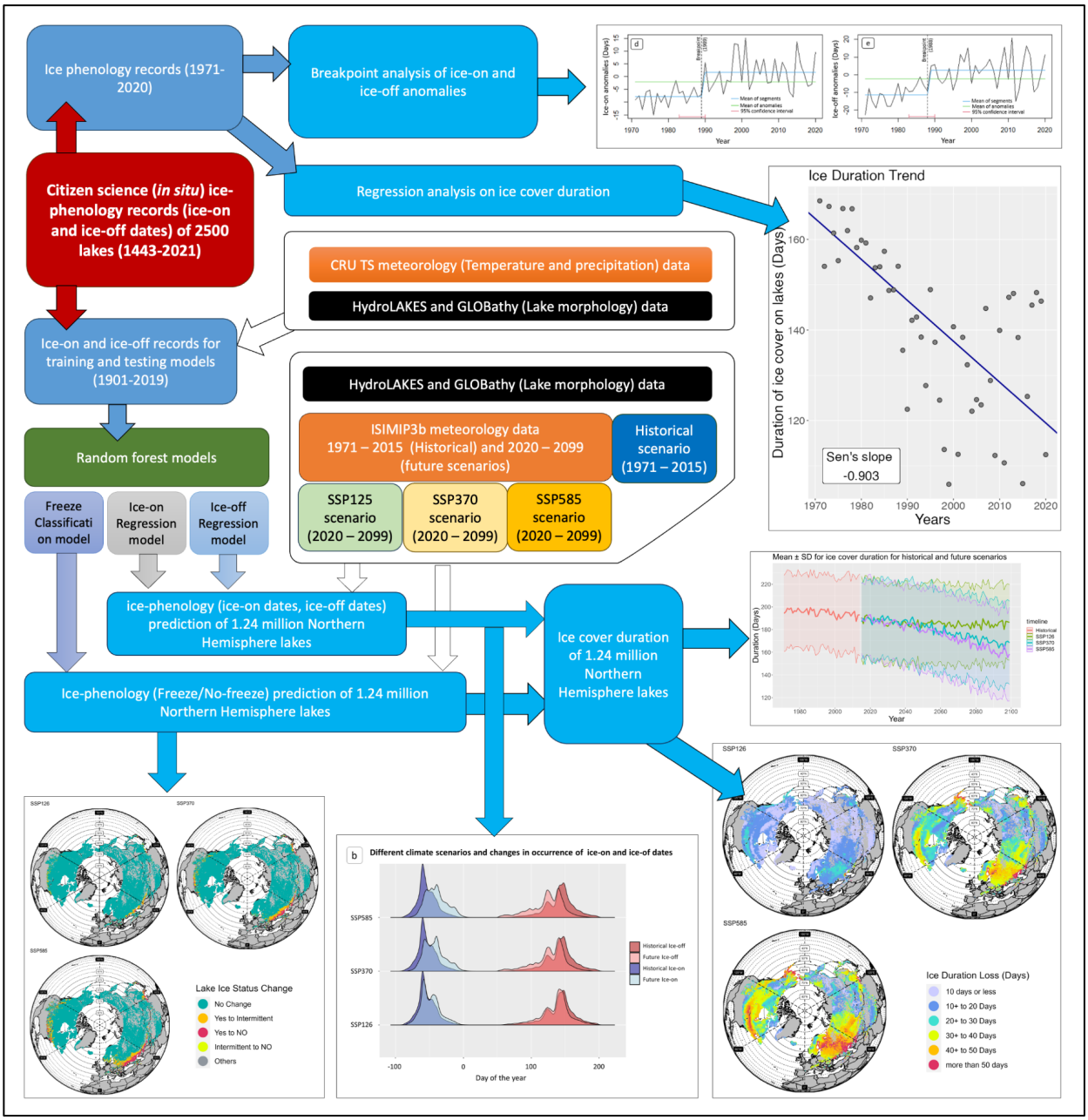


Figure 2: Schematic outline of the study. The study can be divided into two major sections: i) historically observed change in ice phenology and training models with *in situ* data, and ii) projecting future and historical ice phenology for lakes across the Northern Hemisphere.

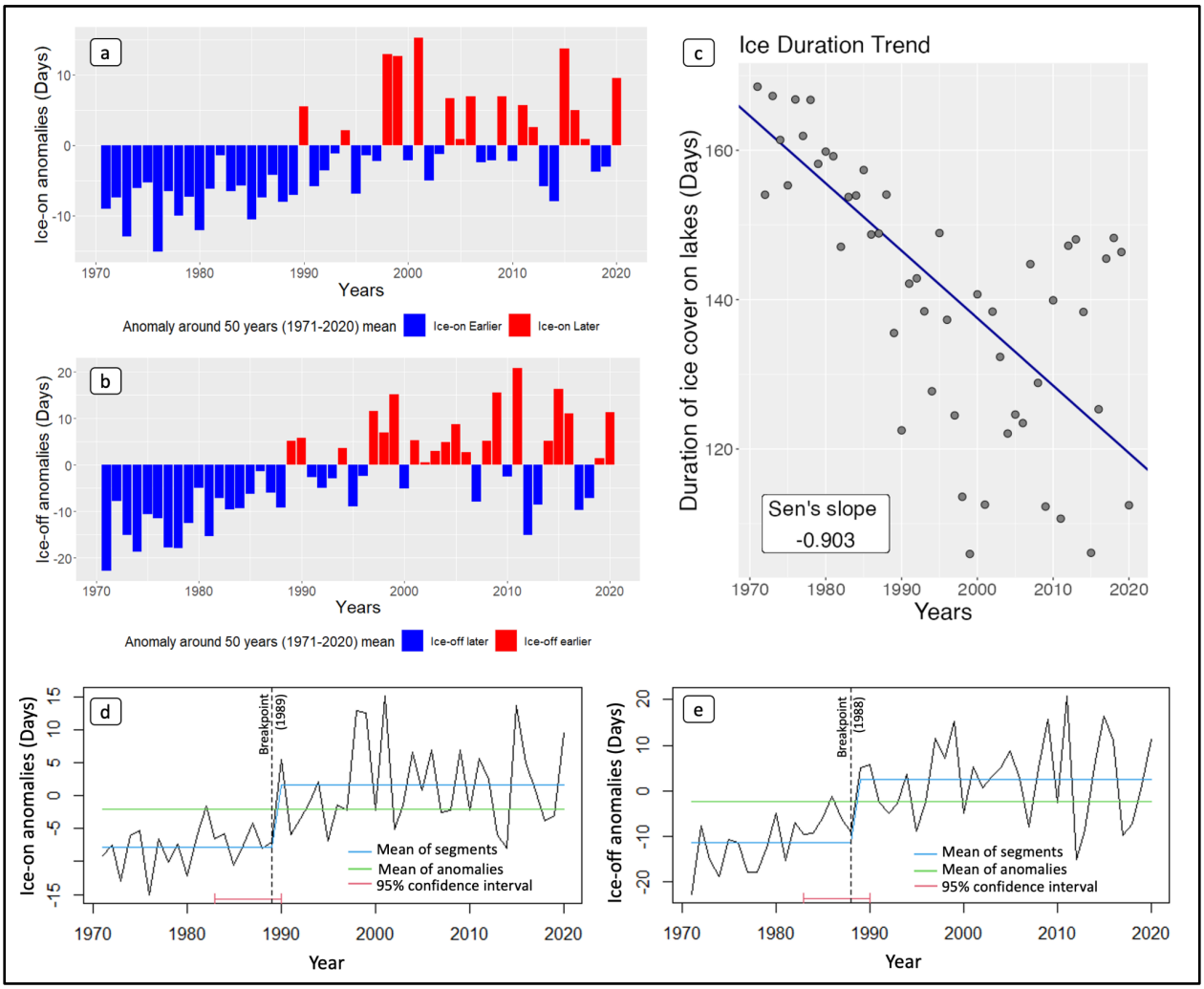


Figure 3: State of Northern Hemisphere Lake ice-on and ice-off for years 1971-2020: a) Ice-on anomalies in days, b) Ice-off anomalies in days, c) Linear trend in duration over the 50 years, Time series showing breakpoints and means of the phenology anomalies before and after the breakpoint for d) Ice-on anomalies calculated from 1,899 lakes and e) Ice-off anomalies calculated from 2,397 lakes.

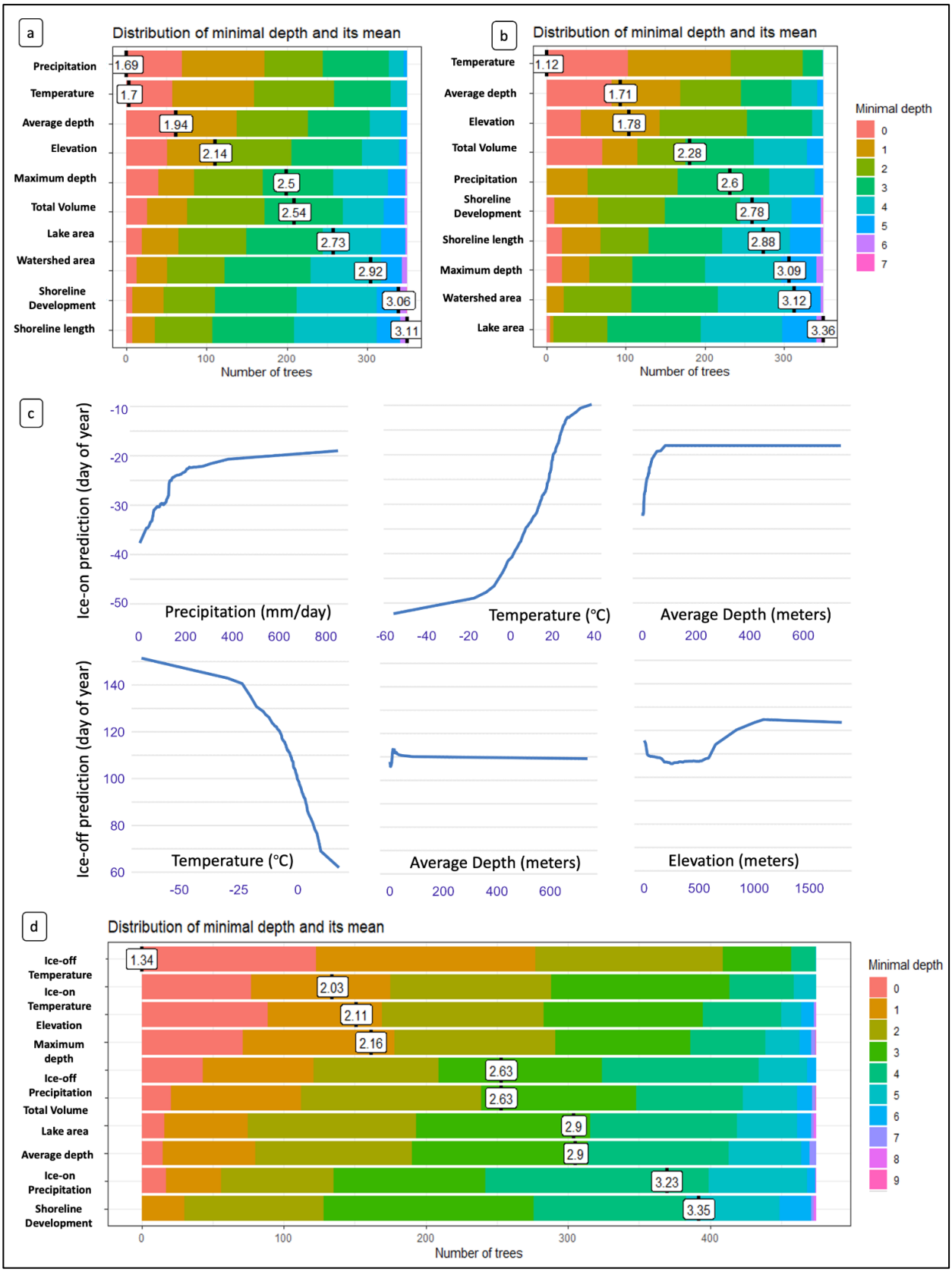

a
Distribution of minimal depth and its mean
Precipitation
Temperature
Average depth
Elevation
Maximum depth
Total Volume
Lake area
Watershed area
Shoreline Development
Shoreline length
1.69
1.7
1.94
2.14
2.5
2.54
2.73
2.92
3.06
3.11
0
100
200
300
Number of trees
b
Distribution of minimal depth and its mean
Temperature
Average depth
Elevation
Total Volume
Precipitation
Shoreline Development
Shoreline length
Maximum depth
Watershed area
Lake area
1.12
1.71
1.78
2.28
2.6
2.78
2.88
3.09
3.12
3.36
0
100
200
300
Number of trees
Minimal depth
0
1
2
3
4
5
6
7
c
Ice-on prediction (day of year)
-10
-20
-30
-40
-50
Precipitation (mm/day)
0
200
400
600
800
Temperature (°C)
-60
-40
-20
0
20
40
Average Depth (meters)
0
200
400
600
Ice-off prediction (day of year)
140
120
100
80
60
Temperature (°C)
-50
-25
0
Average Depth (meters)
0
200
400
600
Elevation (meters)
0
500
1000
1500
d
Distribution of minimal depth and its mean
Ice-off Temperature
Ice-on Temperature
Elevation
Maximum depth
Ice-off Precipitation
Total Volume
Lake area
Average depth
Ice-on Precipitation
Shoreline Development
1.34
2.03
2.11
2.16
2.63
2.63
2.9
2.9
3.23
3.35
0
100
200
300
400
Number of trees
Minimal depth
0
1
2
3
4
5
6
7
8
9

Figure 4: Importance of predictor variables based on random forest models. a) Minimal depth distribution plot for ice-on model. b) Minimal depth distribution plot for ice-off model. c) Partial dependence plots for the three most important ice-on variables (top row) and ice-off variables (bottom row). d) Minimal depth distribution plot for freeze/no-freeze classification model. Here, all variables in the variable importance plot are arranged in descending order of importance.

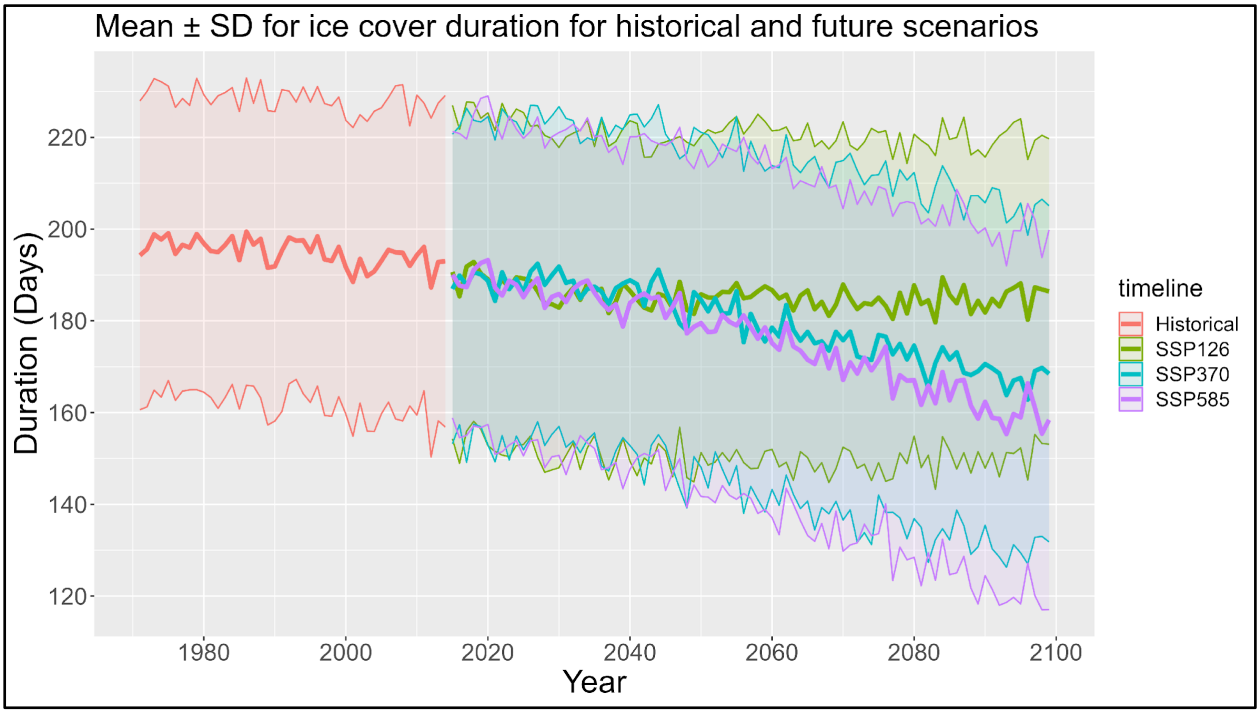


Figure 5: Ice duration change for historical (1971-2015) and three future (2016 - 2099) SSP scenarios. Here, the thicker line represents the mean of ice cover duration of 1.12 million lakes. The thinner lines, containing the shaded area, denote the upper and lower bounds of the standard deviation of duration observed for the 1.12 million lakes.

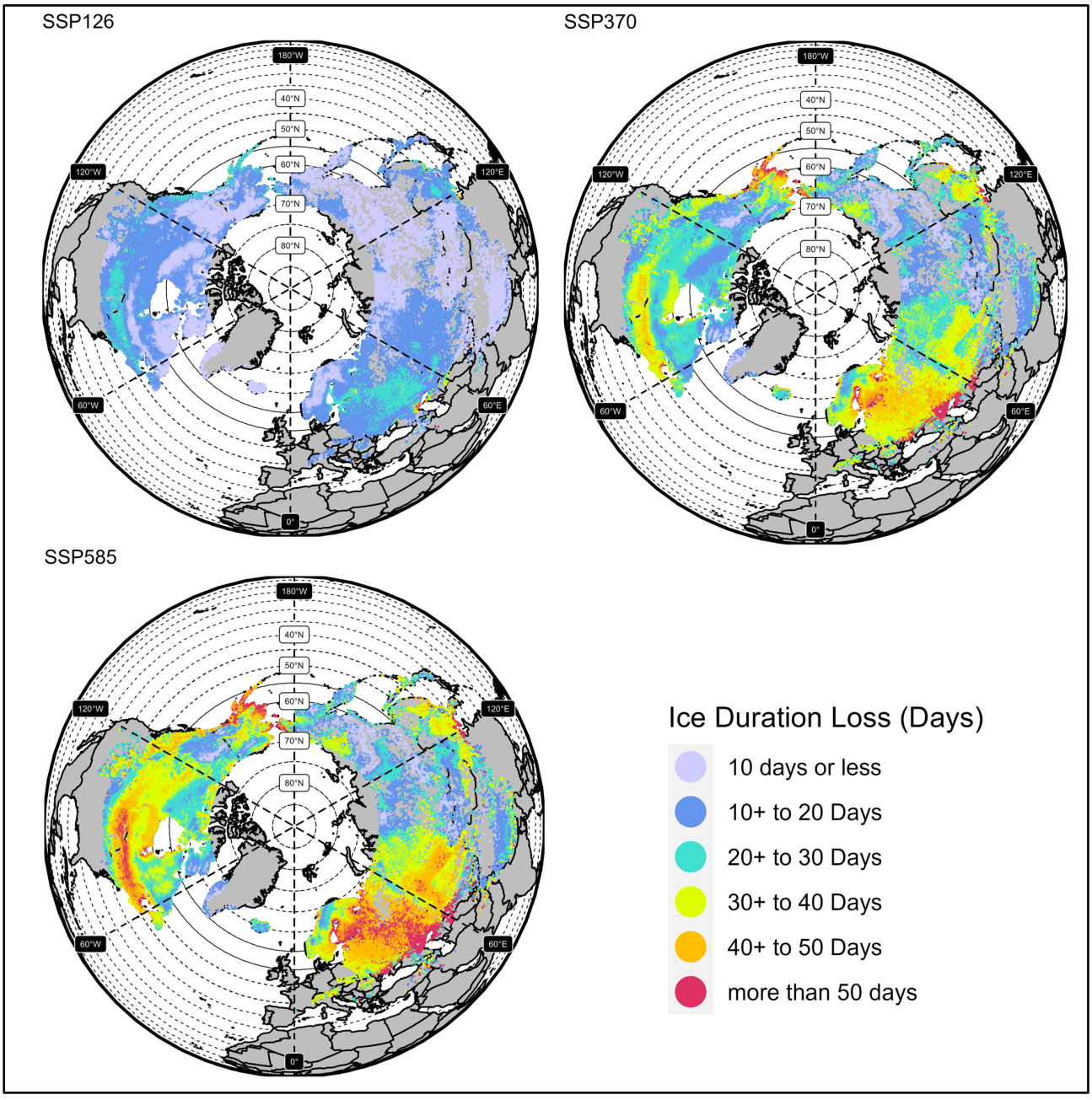


Figure 6: Projected spatial distributions of change in lake ice cover duration for future (2070-2099) SSP climate change scenarios in comparison to Historical (1971-2000) period.

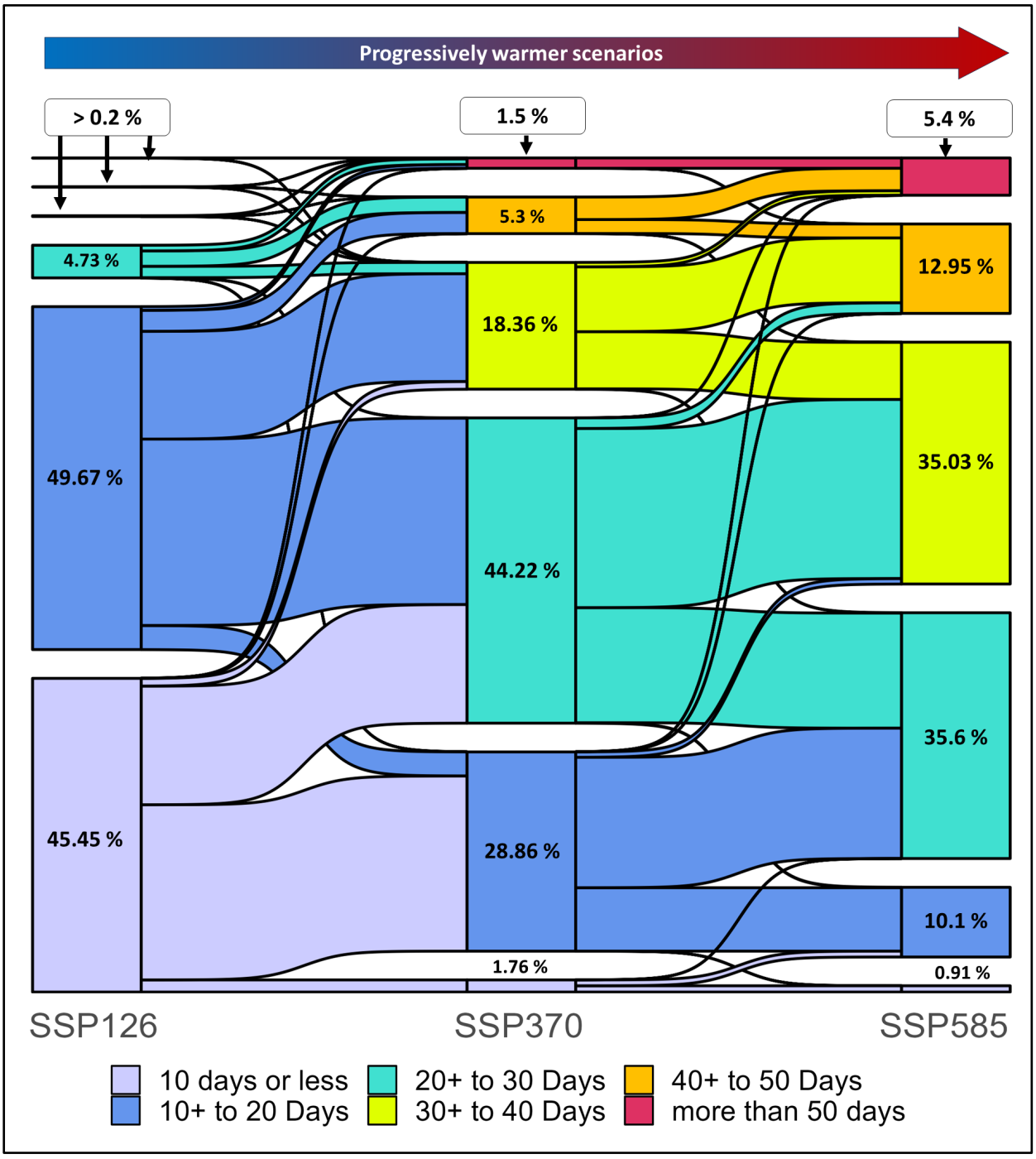


Figure 7: Sankey diagram of SSP126, SSP370, and SSP585 scenarios ice cover duration change (averaged over the period 2070-2099) compared to the Historical period (averaged over the period 1971-2000) depicting transitions in lake duration groups in progressively warmer climate scenarios. While some lakes remain in the same duration group, many lakes transition from

longer duration groups to shorter duration groups as one moves across this diagram from Historical to SSP585.

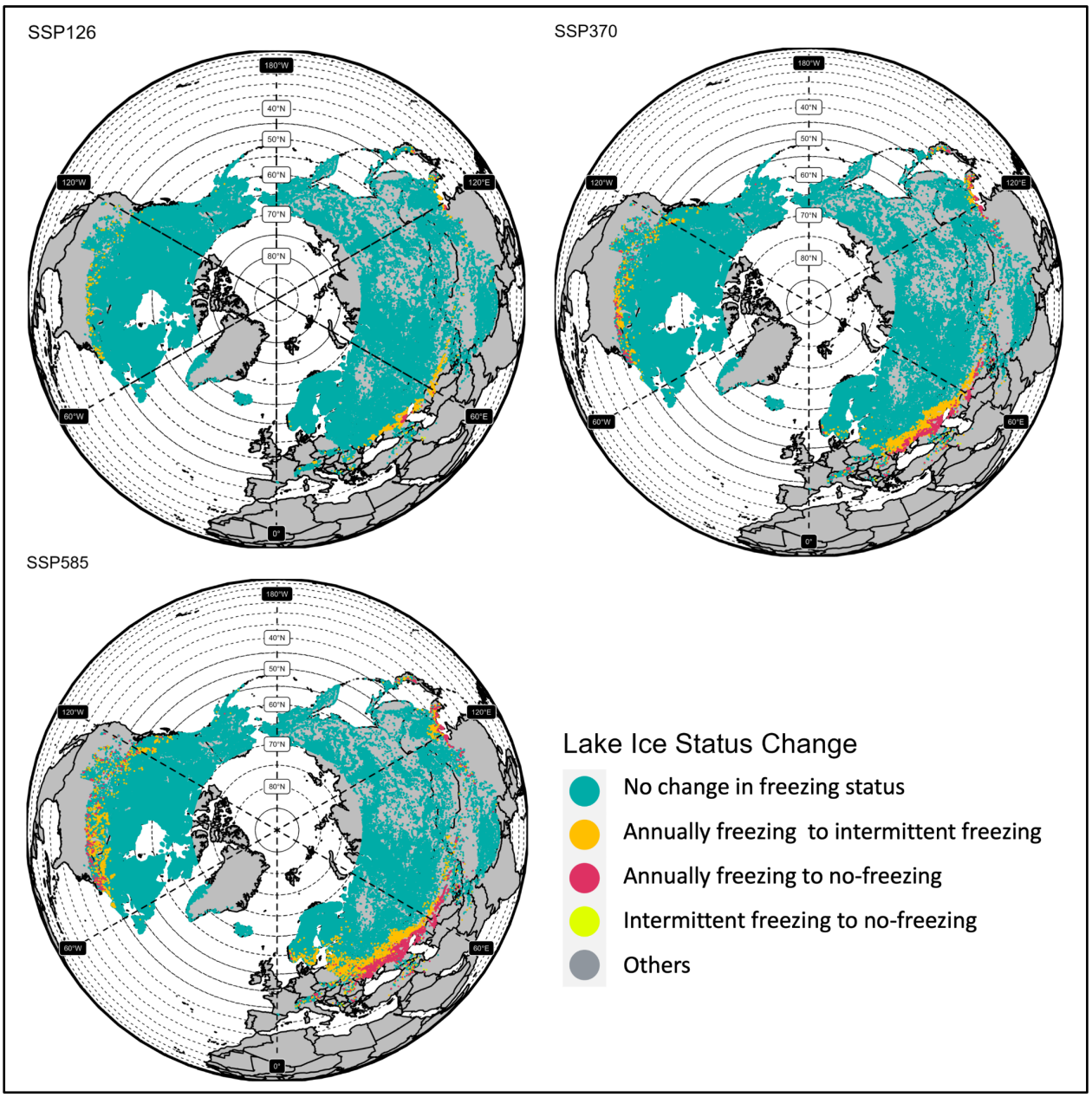


Figure 8: Spatial distribution of changes in lake categories observed between historical (1971-2000) and future (2070-2099) SSP climate scenarios. Here, Annual freezing denotes when the lake freezes continuously without an ice-free year; intermittent freezing denotes lakes

experiencing at least one ice-free year, and no freezing denotes lakes that are no longer reliably freezing with 50% or more years are ice-free.

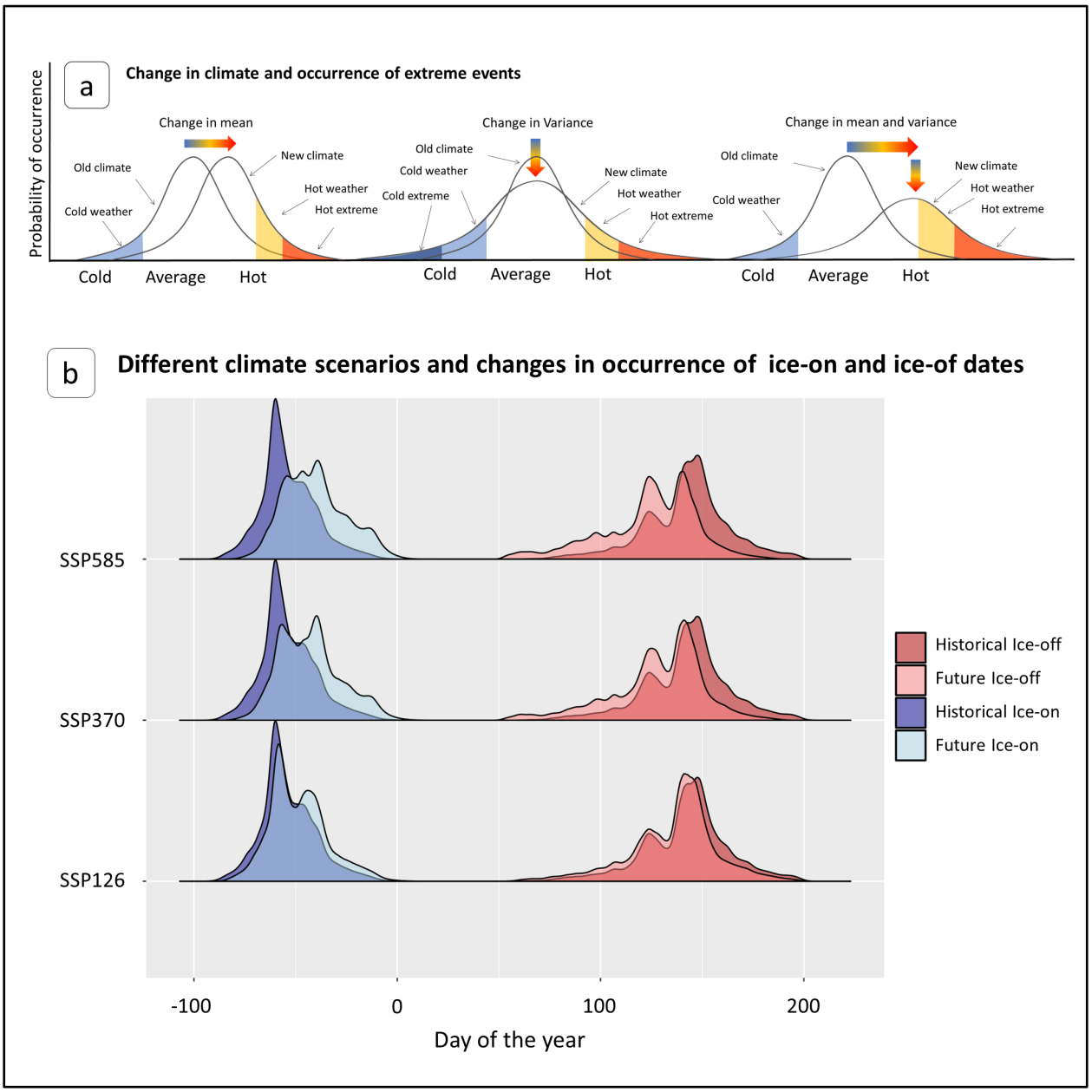


Figure 9: Change in ice phenology with changing climate, a) Impacts of changes in climate and occurrence of extreme events on ice phenology (Adapted and modified from Benson et al., 2012) and b) Ridge plot comparing historical and future changes in ice-on and ice-off dates for three SSP scenarios.

Chapter 3: Unsafe Lake Ice Under Climate Change: Forecasting Lake Ice Quality for 1.12 Million Lakes Across the Northern Hemisphere.

Aman Basu, Kevin Vikström, Joshua A. Culpepper, Faith R. Ferrato, R. Iestyn Woolway, Sapna Sharma

Author's Contributions

AB, KV, and SS conceived the research ideas and designed the study. AB developed the methodology, conducted the investigation, performed validation and formal analyses, curated the data, and produced the visualizations. AB and SS contributed resources. KV and SS provided supervision, SS managed project administration, and secured funding. AB and KV wrote the original draft, and AB, KV, SS, FF, JC, and IW participated in the review and editing. All authors contributed to successive drafts and approved the final manuscript for publication.

Summary

The quality of lake ice governs both ecosystem function and winter safety. Yet, there are currently no global assessments projecting ice quality changes under future climate scenarios. Using 23,613 field measurements collected from 140 lakes across 11 countries, we trained machine learning models and applied them to 1.12 million ice-covered lakes around the Northern Hemisphere. Projections under three Shared Socioeconomic Pathways (SSP126, SSP370, and SSP585) revealed widespread declines in ice quality by the late 21st century, with black ice declining up to 4 cm and the proportion of white ice increasing. These changes are projected to decrease load bearing strength by up to 1414 kg, leaving as many as 578 million people living in areas with hazardous ice conditions. Our findings provide the first global projection of lake ice quality, highlighting how climate warming is endangering ecosystems and the human communities they support.

Introduction

Approximately 1.1 billion people live near lakes that freeze over in winter (Hampton et al., 2024). For many of these communities, lake ice is crucial to cultural and religious practices, as well as livelihoods (Knoll et al., 2019; Magnuson & Lathrop, 2014). In northern regions, stable ice cover provides access to hunting grounds and facilitates transportation via trails and ice roads in remote locations (Barrette et al., 2022; Ford et al., 2023; Knoll et al., 2019). Activities on frozen lakes, such as ice fishing, skating, skiing, and testing sites for winter driving, further support the local economy (Filazzola et al., 2024; Hampton et al., 2024), contributing over $2.04 billion annually across communities in the Northern Hemisphere (Filazzola et al., 2024). However, climate change is altering our economic and cultural ties to lake ice, as the timing of ice cover has become more unpredictable (Sharma et al., 2021). Shorter ice seasons (Woolway et al., 2022), and thinner, weaker ice (Sharma et al., 2020; Vikström et al., 2025) are making traditional and recreational activities on lakes less viable and more hazardous.

The use of lake ice depends on the duration of ice cover, ice thickness, and the quality of the ice sheet (i.e., the ratio of black to white ice). Reduced ice cover duration shortens the overall time available for ice-related activities, and the combined factors of ice thickness and quality determine whether the ice sheets are strong enough to support these activities (Weyhenmeyer et al., 2022). For instance, 15 cm of ice is considered safe for standing and skating, while 25 cm is needed for snowmobile use (Canadian Red Cross, 2014; Government of Alberta, 2024). Although safety guidelines are founded on total ice thickness, all strongly advise testing the ice's stability before usage to account for the effect of ice quality. Ice quality is crucial in assessing ice stability, as white ice has approximately half the load-bearing strength of black ice of equal thickness at -0.5 °C (Barrette, 2011; Gold, 1971), a difference that arises from their distinct formation processes. Black ice forms large, transparent crystals (Michel & Ramseier, 1971) as heat is conducted from the ice-water interface and released into the atmosphere (Leppäranta, 2023), resulting in structurally stronger ice. In contrast, white ice forms small, randomly oriented crystals, primarily through the refreezing of snow and slush on the ice surface that is superimposed on the black ice layer (Leppäranta, 2023). This structure makes white ice weaker, meaning that a sheet of white ice may support less weight than a thinner layer of black ice,

particularly at warmer temperatures (Barrette, 2011). As a result, total ice thickness alone is an insufficient measure of ice stability.

While declining ice thickness does not necessarily imply weaker ice, it remains a strong indicator of reduced ice strength, as a warmer climate may strongly affect the structurally robust black ice due to its formation process (Culpepper, Jakobsson, et al., 2024). Lake ice thickness has decreased at an average rate of 1.2 cm per decade in North American lakes from 1962 to 2020 (Imrit et al., 2022), 2.2 cm per decade in Swedish lakes from 1960 to 2009 (Vikström et al., 2025), and 2.4 cm per decade in Finnish lakes from 1910 to 2024 (Culpepper, Jakobsson, et al., 2024). By the end of the 21st century, it is projected that lake ice thickness will decrease by an average of 35 cm across the Northern Hemisphere under the Representative Concentration Pathway (RCP) 8.5 (Li et al., 2022) and 23 cm globally under the Shared Socioeconomic Pathway (SSP) 3-7.0 (Huang et al., 2022). The ongoing and projected decline in ice thickness could result in more hazardous ice conditions than thickness alone implies, as the proportion of weaker white ice relative to black ice is expected to increase (Weyhenmeyer et al., 2022), even as overall ice thickness decreases. In this context, Culpepper, Huang, et al. (2024) have argued that changes in ice quality might extend the unsafe period of ice cover more than warming alone.

In situ ice quality observations are essential for predicting future changes in ice quality and load-bearing capacity at a global scale. However, studies that quantitatively assess changes in ice quality and their drivers using such *in situ* data remain scarce (Weyhenmeyer et al., 2022), and no global projection of ice quality currently exists. As a result, there is no planetary-scale assessment of how climate change will affect the load-bearing capacity of lake ice, informed by modeled black and white ice thickness projections. In this study, we compiled a comprehensive global dataset of ice quality measurements, developed ice quality models using meteorology, lake morphology, and land use drivers, and applied them to project future ice quality and load-bearing capacity across the Northern Hemisphere, highlighting the potential risks to ice safety under divergent climate scenarios. More specifically, in this study, we asked: 1) How is lake ice quality forecasted to change under varying Shared Socioeconomic Pathways (SSP) climate scenarios? and 2) What regions of the Northern Hemisphere will be able to support traditionally held ice-dependent human activities in the future, and will hazards associated with those activities increase?

Methods

1. Data acquisition

This study used ice quality, meteorology, lake morphology, land use, and human population projection databases to build ice quality models, project ice conditions, and evaluate risks related to on-ice activities (Supplementary Table 1). For model development, we selected datasets with global coverage that accurately reflect ground conditions and have sufficient temporal coverage to be paired with *in situ* ice quality observations. For projecting ice conditions from historical to multiple future scenarios, the datasets are chosen to align with the Shared Socioeconomic Pathways (SSP) climate projections.

Ice quality data were compiled from both primary and secondary sources (Supplementary Table 2). The primary data were collected from weekly sampling of Paint Lake, Ontario, Canada (45.22221, -78.94491) and Lake Simcoe, Ontario, Canada at Kempenfelt Bay (44.39218, -79.59935) between January and March 2024, while the remaining came from secondary data sources (Supplementary Figure 1; Supplementary Table 2) which were openly available online, available on request, or estimated from publication figures using WebPlotDigitizer (Rohatgi, 2024). We collected ice quality data for 140 lakes covering 11 countries, with an average of 18 years of data. Multiple measurements of ice quality were available for 118 of the 140 total lakes, with a mode of three measurements per season. The aggregated data resulted in 23,613 ice quality measurements. These ice quality data average ten observations per winter per measurement site that delineate between white ice, black ice, and total thickness (in cm), alongside sampling dates and locations. We found that 13.7% of all measurements of white and black ice thicknesses do not perfectly match the observed total thickness, with a median absolute deviation of 6 cm between the total thickness and the sum of the black and white ice thicknesses. Ideally, the total length of an ice column should equal the sum of the black and white ice thicknesses, but often due to unclear white ice - black ice boundary or due to existence of multiple slush layers within the ice sheet, a discrepancy between the total thickness and the sum of the thicknesses of the individual ice types may occur (See supplementary image 1). To maintain consistency throughout the ice quality dataset (*sensu* Vikström et al., 2025), we inferred white ice thickness by subtracting black ice thickness from the total thickness for cases where the sum of black and white ice thicknesses did not equal the total thickness.

We extracted meteorological variables from ERA5-Land (Muñoz Sabater, J., 2019) using Google Earth Engine (Gorelick et al., 2017) with a spatial resolution of 11.132 km for each lake, including daily average, maximum, and minimum air temperature (K) (2 m above the surface); daily cumulative sum of total precipitation in the form of rain or snow (m day^{-1}); daily cumulative sum of snowfall (m of water equivalent); daily cumulative sum of incident shortwave solar radiation (J m^{-2}); and northward and eastward components of the 10 m above the surface wind speed (m s^{-1}). For historical and future climate scenario projections, daily average near-surface (2 m above the surface) air temperature (K), daily maximum near-surface air temperature (K), daily minimum near-surface air temperature (K), total precipitation flux in the form of rain or snow (kg m^{-2} s^{-1}), snowfall flux (kg m^{-2} s^{-1}), surface downwelling shortwave radiation (W m^{-2}), and near-surface (10 m above the surface) wind speed (m s^{-1}) were obtained for the period 1971 to 2099 for three SSPs climate scenarios from Inter-Sectoral Impact Model Intercomparison Project (ISIMIP) data repository ("ISIMIP3b bias-adjusted atmospheric climate input data," 2021). We employed the following SSP scenarios: SSP126, SSP370, and SSP585 for historical comparison and future ice quality projections. The meteorological variables are further refined by combining daily maximum and minimum temperatures into a single variable: temperature range (the difference between maximum and minimum). Additionally, total precipitation was separated into two variables: rainfall (total precipitation minus snowfall) and snowfall amount.

Lake morphological information was obtained from the HydroLAKES database, including area (km^2), shoreline length (km), shoreline development (i.e., ratio of shoreline length and circumference of a circle with the lake's area), total volume (m^3), average depth (m), and elevation (m.a.s.l.) (Messager et al., 2016). Eighty-seven of the total 140 lakes had sampling coordinates within a HydroLAKES polygon. We manually matched 25 of the remaining 53 lakes by checking the sampling location and the nearest HydroLAKES polygon boundary, or by matching the lake name and country. We were unable to match the remaining 28 lakes due to the lake being smaller than s 0.1 km^2 surface area or if the geographic location information indicated the waterbody was located on a river or landmass; therefore, the resulting database includes 112 lakes. A total of ten lakes have multiple sites with measurements on the same day. In such cases, we averaged all observations collected on the same day to represent that lake's ice quality values.

We extracted six land-use categories from the HILDA+ Global Land Use Change database, which has a 1 km spatial resolution and covers the period from 1960 to 2019 (Winkler et al., 2021). These variables included urban, cropland, pasture/rangeland, forest, unmanaged grass or shrubland, and sparse or no vegetation. The percentage coverage of each land cover type was calculated from a 10 km buffer zone outside the lake polygons obtained from HydroLAKES (Hillman & Nielsen, 2025). If the lake ice record fell outside the 1960-2019 temporal range of the HILDA+ dataset, land-use values were matched to the nearest year. To ensure consistency between historical and future Shared Socioeconomic Pathway (SSP126, SSP370, and SSP585) scenarios, we used land use data from the Land-Use Harmonization 2 (LUH2) database (Hurtt et al., 2022). A total of twelve land use categories were extracted from LUH2 (Hurtt et al., 2022) for the period 1971-2099: forested primary land, non-forested primary land, potentially forested secondary land, potentially non-forested secondary land, managed pasture, rangeland, urban land, C3 annual crops, C3 perennial crops, annual crops, perennial crops, and nitrogen-fixing crops. To maintain consistency between HILDA+ land use data (Winkler et al., 2021), used for modeling, and LUH2 land use data (Hurtt et al., 2022), used for future projections, we combined categories from both datasets into five primary land-use classes: Urban, Cropland, Forest, Grassland, and Barren (see Supplementary Table 3), based on the work of Chen et al. (2022).

Population data were not available for the sub-scenarios of SSP126, SSP370, or SSP585; therefore, we extracted 1-km gridded population count data for the SSP1, SSP3, and SSP5 scenarios, projected in 5-year intervals between 2070 and 2100, from Wang et al. (2022).

2. Data analysis

2.1. Building ice quality models using machine learning algorithms

Seventeen predictor variables, including six meteorology, six lake morphology, five land use, plus an additional ice quality measurement day-of-year predictor, totaling 18 predictors, were used to develop the ice quality models. The day of the year variable was included to account for the sequential development of black ice and white ice, as black ice forms first to enable the development of superimposed white ice. We represent the measurement date as the day of year (DOY), starting on September 1 (e.g., Jan. 1 is DOY 123).

To account for the influence of weather condition effect on ice quality, we computed 17 mean antecedent periods, in days, for each meteorological variable: 1, 3, 7, 15, 30, 45, 60, 75, 90, 105, 120, 135, 150, 165, 180, 195, and 210. For example, an antecedent of 3 for air temperature is based on the mean air temperature of the three days preceding the sampling date. We used each of the 17 antecedent periods to build separate black ice and white ice models.

We tested five machine learning regression models: Elastic Net (Friedman and Tibshiran, 2010), General Additive Model (GAM) (Wood, 2011), Decision Tree (Therneau and Atkinson, 2023), K-Nearest Neighbors (KNN) (Kuhn, 2008), and Random Forest (Liaw and Wiener, 2002) using the R statistical environment (R Core Team, 2024). We used 80% of the data as the training set and 20% for the testing set, where models were built with ten-fold cross-validation to correct for overfitting (Allgaier and Pryss, 2024) using the caret package (Kuhn, 2008). We extracted the mean absolute error (MAE), root mean square error (RMSE), and R-squared values from the testing set to determine the model's fit. We selected the antecedent value and machine learning model that produced the highest R-squared value, the lowest MAE, and the lowest RMSE for ice quality projections.

2.2. Ice quality projections, allowable load estimates, and risk estimations

Projections of ice quality were generated for 1.12 million lakes across the Northern Hemisphere for lakes that are ≥0.1 km² in area (Messager et al., 2016), situated below 70°N latitude, and experiencing average winter air temperatures below –0.4°C (Sharma et al., 2019; Weyhenmeyer et al., 2004). The projection period spans 1971 to 2099. Since the predictive model was trained on ice quality data rather than ice phenology, ice-on and ice-off dates were derived from Basu et al. (2024), and our model predicted ice quality during the ice-cover period. The original *in situ* measurements used to train the model were collected when ice was stable enough to measure thickness and quality safely, suggesting that the model does not estimate ice quality outside these conditions. Analyses by Culpepper, Huang, et al. (2024) of lake ice thickness data from the Community Earth System Model Version 2 Large Ensemble (CESM2-LE; Rodgers et al., 2021) indicated that historically (1851–1880), safe ice thickness typically occurred from six days after ice-on until four days before ice-off. Consequently, this stable-ice period was adopted for ice quality projections in this study. Ice thickness was recorded as zero for years when lakes did not freeze or when the safe freezing window was shorter than 11 days.

We used the seasonal average values to represent the ice quality of a lake over the course of a year. We observed changes in ice quality by measuring the difference between the 30-year historical average (1971-2000) and the 30-year future averages (2070-2099) for different SSP scenarios. We calculated Sen's slope and tested for the significance of a monotonic trend using the Mann-Kendall test over the period 2015-2099 to estimate future trends, utilizing the R package "trend" (Pohlert, 2023).

We forecasted the load-bearing capacity across the Northern Hemisphere. To estimate the load-bearing capacity of the ice, we used Eq. (1) from Weyhenmeyer et al. (2022).

$$P = \frac{A \cdot H^2}{2} \cdot \left(1 + \frac{100 - \%\,White\ ice}{100}\right) \qquad \text{Eq. (1)}$$

Here, P is the allowable load in kg, H is the total ice thickness in cm, and % white ice is the percentage of white ice in the total thickness. A is the bearing strength, which corresponds to 3.5 to 17.5 kg cm^{-2}, depending on the quality of the ice (Gold, 1971). Our study used 3.5 kg cm^{-2}, the most conservative value for calculating the allowable load and inferring the ice safety situation.

To evaluate the future risks linked to lake ice activities, we examined the expected changes in load-bearing capacity and the anticipated distribution of the human population in the area. We measured the mean load-bearing capacity of lakes for the period 2070-2099, considering 2° hexagonal grids across the entire projected lake area. Since the population projections from Wang et al. (2022) are available in 5-year intervals, we calculated the mean population for the years 2070-2100 and each grid area. To visualize the data and ensure that scenarios were comparable, we divided the load capacity of SSP370 and the projected population of SSP3 into three equal quartiles. We used a three-by-three bi-variate color scale with the R package "biscale" (Prener et al., 2022) to represent the scenarios. We also estimated the total number of people experiencing different degrees of change in load-bearing capacity across the three groups of load capacity loss (high, mid, and low).

Results

Among the five machine learning models tested, random forest models performed the best, as they yielded the highest R-squared and the lowest MAE and RMSE values for both black

and white ice thickness models (Supplementary Figure 2a). The best performing models were based on 75 days of antecedent meteorological data for black ice and 120 days for white ice (Supplementary Figure 2a). On the testing dataset, the black ice random forest model with 75 days of antecedent meteorological data explained 81% of the variation in black ice thickness (R^2 = 0.81; MAE = 5.74; RMSE = 7.73; Supplementary Figure 2b), whereas the white ice model with 120 days of antecedent meteorological data explained 70% (R^2 = 0.7; MAE = 3.77; RMSE = 5.68; Supplementary Figure 2b). Both models drew on the same set of predictors, using a combination of meteorological, morphological, land use, and day of the year variables. These two models were therefore utilized to project ice quality. Further investigation of these two models revealed that average air temperature, snowfall, and rainfall were the most influential predictors (Supplementary Figure 3a). Increasing average air temperature and rainfall lead to decreased thicknesses of white and black ice, while more snowfall promotes white ice growth but reduces black ice thickness (See supplementary Figure 3b). Overall, meteorological predictors primarily determine lake ice quality, followed by distinctly less important but similarly influential morphology and land-use variables (Supplementary Figure 3c).

1. How is lake ice quality forecasted to change under varying Shared Socioeconomic Pathways (SSP) climate scenarios?

Both black and white ice are expected to decline under all SSP climate scenarios across the Northern Hemisphere, indicating an overall reduction in ice thickness (Figure 4a,b). In the SSP126 scenario, the decrease in black ice will be relatively minimal, showing signs of recovery toward the end of the century (Figure 1a), while total white ice thickness remains similar to the historical average (Figure 1b). In contrast, under SSP370 and SSP585 scenarios, black ice will decline steadily throughout the century (Figure 1a), with white ice also trending downward (Figure 1b). Spatially, under the SSP126 scenario, white ice thickness is expected to decrease slightly (0+ to 2.5 cm) across much of the Northern Hemisphere, but may increase between 50°N and 60°N in North America and parts of Russia (Figure 1c). Conversely, black ice thickness will decrease across most of the Northern Hemisphere by a similar magnitude (0+ to 2.5 cm), along with larger declines (2.5+ to 5 cm) in southern regions of North America and Europe (Figure 1c). Under SSP370 and SSP585 scenarios, changes in white ice thickness become more variable, exhibiting both increases and decreases (Figure 1d,e). Black ice thickness, by contrast, shows the

most pronounced declines in southern latitudes and coastal regions, particularly across Europe and in lakes between 40-50°N in North America (Figure 1d,e).

The proportion of white ice within the ice column is expected to increase by 0.62%, 0.95%, and 1.11% under the SSP126, SSP370, and SSP585 scenarios, respectively, across Northern Hemisphere lakes (Supplementary Figure 4a). From a spatial perspective, while some regions of the Northern Hemisphere may experience a decrease in the percentage of white ice within the ice column, most areas are expected to show an overall increase (Supplementary Figure 4b,c,d). The observed increase in white ice percentage is more prominent under the SSP370 and SSP585 scenarios. Coastal regions, all of Europe, and regions between 40-50°N in North America are projected to experience a higher proportion of white ice relative to black ice compared to the historical period. In particular, Europe is likely to see a higher percentage of white ice under the warmer SSP370 and SSP585 scenarios than under SSP126. While the white ice percentage is projected to increase, the thickness of both white and black ice (i.e. total ice thickness), will likely decrease in those regions (Figure 1a,b).

Among the SSP scenarios, SSP126 will see the least change, while SSP370 will experience the most significant qualitative change in ice between 2015 and 2099. Under SSP126, most lakes (64.5%) show no significant trend in both black and white ice thickness, suggesting that overall thickness, strength, and ice quality remain similar to historical levels for most of the Northern Hemisphere (Figure 2a,d). In the warmest scenario, SSP585, 54.6% of the lakes are expected to experience a significant decline in both black and white ice, likely resulting in much thinner and weaker ice compared to SSP126, but with similar ratios, as both white and black ice are anticipated to decrease (Figure 2c,d). In contrast, under the SSP370 scenario, nearly half of the lakes (49%) will fall into the category that exhibits decreasing black ice thickness while white ice remains unchanged, leading to thinner and weaker ice with unprecedented ice quality conditions (Figure 2b, d).

2. Which regions of the Northern Hemisphere will be able to support traditional ice-dependent human activities in the future, and will hazards associated with those activities increase?

The projected average loss of bearing strength for the end of the century (2070-2099) is 487 kg, 1103 kg, and 1414 kg under SSP126, SSP370, and SSP585 scenarios, respectively,

compared to the historical average (1971-2000). Under SSP126, reductions in allowable load will stabilize by the end of the century, whereas in the warmer SSP370 and SSP585 scenarios, it will continue to decline (Figure 3a). In the future SSP126 scenario, most lakes will remain within the 0-1000 kg loss category compared to the historical period (Figure 3b). By contrast, under SSP370 and SSP585 scenarios, larger losses (1000-4000 kg) become more prevalent, especially in the southern latitudes, along with the west coast of North America, the Canadian Arctic, and Europe (Figure 3c, d). When depicted as the absolute value of the allowable load rather than the relative change, the most significant reductions will occur in southern latitudes, with progressively lower allowable loads extending from southern to northern regions as scenarios become warmer (Supplementary Figure 5). Lakes at higher latitudes (60-70°N), remain largely in the load bearing capacity >5000kg category, while the greatest absolute declines are concentrated in Europe, mid latitudes of North America (40-60°N), and coastal regions, particularly under SSP370 and SSP585 scenarios (Supplementary Figure 5c,d).

Only 1.28% of the total population in the projected area will be in the high-risk zone for the SSP126 scenario (Figure 4a,d). However, populations in high-risk areas increase sharply to 52.11% and 65.18% in the SSP370 and SSP585 scenarios, respectively (Figure 4b,c,d). The projected high-risk regions are primarily located within Europe and in areas south of 50 °N in North America. Although the loss of load-bearing capacity will be pronounced in many parts of the Arctic and subarctic regions, the projected population density is low in these regions suggesting a low overall risk of human exposures to hazardous ice conditions.

The SSP126 scenario suggests that approximately 9.76 million people, or 1.3% of the North American population, are expected to experience low levels of change in ice-bearing strength by the end of the 21st century (2070-2100) (Table 1). Therefore, the overwhelming majority of the population (98.7%) will be in low or medium-risk areas. However, in the warmer scenarios, approximately 392 million (52.4%) under SSP370 and 578 million (65.6%) under SSP585 are projected to live in areas where ice-bearing strength considerably declines (Table 1).

Discussion

Our global analysis revealed a widespread decline in lake ice thickness across all climate scenarios, with black ice declining more rapidly than white ice. This shift leads to a higher proportion of structurally weaker white ice and overall thinner ice, particularly under warmer

scenarios. By combining *in situ* observations from 140 lakes with large-scale projections across 1.12 million lakes, this study provides the first comprehensive global assessment of lake ice quality and its response to future warming. These findings demonstrate that climate-driven shifts in ice composition will substantially weaken ice stability, posing growing risks to ecosystems and communities that rely on stable ice for access and connectivity.

1. How is lake ice quality forecasted to change under varying Shared Socioeconomic Pathways (SSP) climate scenarios?

Our findings reveal that black and white ice are changing at different magnitudes, and the proportion of white ice within the ice column is projected to increase in many regions under future climate scenarios, supporting current literature (Culpepper et al., 2024; Korhonen, 2006; Weyhenmeyer et al., 2022). Across the Northern Hemisphere, we project average ice thickness to decrease by 1.6 cm, 3.9 cm, or 5.1 cm, according to SSP126, SSP370, and SSP585 scenarios, respectively. Notably, our most pessimistic scenario (SSP585) projects 5.7 times less ice thickness loss than previous studies predicted (Huang et al., 2022; Li et al., 2022), likely due to differences in the number of lakes modeled and the range of lake sizes considered. While earlier studies projected ice thickness using idealized single representative lakes for each 0.9° × 1.25° computational grid (Huang et al., 2022) or on 1313 lakes larger than 50 km^2 (Li et al., 2022), this study projects for 1.12 million individual lakes over the Northern Hemisphere using lake-specific drivers (e.g., lake area, average depth, etc.), with the majority of the projected lakes being much smaller (median surface area: 0.23 km^2; 1st and 3rd quartiles: 0.14 km^2 and 0.48 km^2). Since smaller lakes are known to be more resilient, losing ice cover (Magee & Wu, 2017; Sharma et al., 2019, Sharma et al., 2020) and thickness (Magee & Wu, 2017) more slowly than larger, deeper lakes, our projected loss of ice thickness is less pronounced than in other studies.

Our modeling results, however, are consistent with long-term *in situ* studies of ice quality, which also show general declines in ice thickness with increases in white ice thickness in some lakes. For example, an analysis of 30 Finnish lakes from 1910 to 2002 found that maximum ice thickness decreased in southern regions but stayed the same or increased in central and northern areas, with some northern lakes experiencing more white ice between 1980 and 2000 (Korhonen, 2006). Similarly, among 21 Swedish lakes studied by Vikstörm et al. (2025), five exhibited an increasing trend in white ice thickness, while most showed a decline in overall ice thickness due

to reductions in black ice. This divergent trend in white ice and total thickness occurs because warm conditions prevent heat loss through the ice-water interface. This accelerates the loss of black ice and overall thickness, while promoting the growth of white ice through the repeated melt-refreeze pattern of snow and slush (Leppäranta, 2023). These processes are especially relevant in the context of climate change, where freeze-thaw events on a frozen lake are expected to become more frequent (Weyhenmeyer et al., 2022), leading to higher proportions of white ice within the ice column. Our findings therefore reinforce these observed dynamics, suggesting that future warming will likely reduce total ice thickness while simultaneously increasing the proportion of white ice. The implications of shifting ice composition extend beyond ecological processes to human safety and infrastructure. Vikstrom et al. (2025) argue that lake ice conditions are safer when white ice and black ice decrease at the same rate, but pose a greater risk when black ice diminishes faster than white ice. Under the SSP370 scenario, our projections suggest that this imbalance could compromise the reliability of traditional ice safety guidelines (at least 10 cm for moving weight and 15 cm for stationary weight; Government of Alberta, 2024) as structurally weaker white ice is projected to increase proportionally within the ice column. Consequently, total lake ice thickness may still meet the recommended threshold while supporting significantly less weight, as white ice bears approximately half the weight of black ice at temperatures near 0°C (Barette et al., 2011). However, under SSP126 and SSP585, black and white ice thickness are projected to decline more uniformly, maintaining a more predictable relationship between total ice thickness and load-bearing strength. Thus, future ice safety assessments must consider the relative contributions of white and black ice, as composition will dictate lake ice stability and safety under a warming climate rather than thickness alone.

2. Which regions of the Northern Hemisphere will be able to support traditional ice-dependent human activities in the future, and will hazards associated with those activities increase?

The load-bearing capacity of lake ice is expected to decline across all future climate scenarios; however, the most conservative warming scenario (SSP126) is projected to experience the least change. Under this scenario, ice conditions are expected to remain sufficient for many traditional winter activities, with only marginal ice loss and associated safety concerns, largely preserving historical patterns. Conversely, under the stronger warming scenarios (SSP370 and

SSP585), substantial regional shifts in ice stability are anticipated. In North America, most ice-related activities that historically occurred in southern latitudes are projected to shift northward, where reductions in load-bearing capacity are less critical. Meanwhile, in Europe, the decline in load-bearing capacity is projected to be more severe, to the extent that many ice-related activities may be completely phased out.

Although reductions in load-bearing capacity are expected across both populated and remote areas in the Northern Hemisphere, it is crucial to interpret the results presented in this study from the perspective of human risk. Regions with dense populations and declining load-bearing capacities represent high-risk zones, as frequent human interactions with hazardous lake ice conditions are more likely to result in accidents and injuries. Conversely, in sparsely populated northern regions, particularly within the Canadian Arctic, reduced load-bearing capacities possess a different but equally critical issue. Many northern and indigenous communities rely on ice roads for connectivity (Barrette et al., 2022; Prowse et al., 2011), making them highly vulnerable to thinning and weakening lake ice. Together, these contrasting risks emphasize the importance of scenario based assessments for evaluating future exposure and adaptive capacity across communities.

Under the SSP126 scenario, which assumes high international cooperation and commitment to sustainable development, only 1% of the Northern Hemisphere's population is projected to reside in high-risk zones. In this conservative scenario, changes in load-bearing capacity remain minimal in the Canadian Arctic, suggesting limited disruption to the livelihood of arctic communities. In contrast, under the SSP585 scenario—representing an extreme warming scenario characterized by continued fossil fuel dependence—65% of the population will be in high-risk zones characterized by densely populated areas and a drastically reduced load-bearing capacity, elevating the risk of ice-related hazards. In the optimistic (SSP126) and pessimistic (SSP585) scenarios, human migration is classified as moderate and high, respectively, providing greater flexibility for adaptation through relocation (Wang et al., 2022). The SSP370 scenario, however, presents a more complex challenge. Characterized by limited international cooperation, high regional conflict, low migration (Wang et al., 2022), and substantial challenges for mitigation and adaptation (O'Neill et al., 2017), this scenario places 52% of the population in high-risk regions. As a result, the lack of adaptive capacity through

relocation may exaggerate social and economic consequences of unstable lake ice under SSP370, despite lower overall warming compared to SSP585.

Looking ahead, both the SSP370 and SSP585 scenarios will amplify the challenges faced by northern communities. The growing instability and unpredictability of these vital connections threaten to isolate communities and disrupt essential supply chains, demanding new solutions and the expansion of costly infrastructure to maintain services (Barrette et al., 2022; Gädeke et al., 2021; Hori et al., 2018; Mullan et al., 2017). Beyond northern regions, thinning and hazardous lake ice will also increase the risk of accidents and drownings among populations engaging in traditional winter activities near lakes (Sharma et al., 2020; Woolway et al., 2020). Overall, our findings underscore that the future of lake ice, and the safety and livelihoods it supports, will be actively shaped by climate warming, as well as the societal pathways we choose. The divergence among SSP scenarios highlights that proactive global cooperation, sustainable development, and adaptive planning can substantially mitigate the associated risk with deteriorating ice quality. Accordingly, policymakers and stakeholders must recognize lake ice as a vital component of northern infrastructure and culture, integrating its preservation and adaptation into climate strategies.

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Figure and Tables

Table 1: Projected number of individuals residing in areas with low, medium, and high lake ice load carrying capacity loss by the end of the 21st century.

Future climate scenario	Total population in the projected area (million)	Population in different levels of change in the load-bearing capacity of lake ice		
		Low change (million, %)	Medium change (million, %)	High change (million, %)
SSP126	752	562 (74.8%)	172 (22.9%)	9.6 (1.3%)
SSP370	747	114 (15.3%)	235 (31.5%)	389 (52.1%)
SSP585	882	53.9 (6.1%)	245 (27.9%)	574 (65.1%)

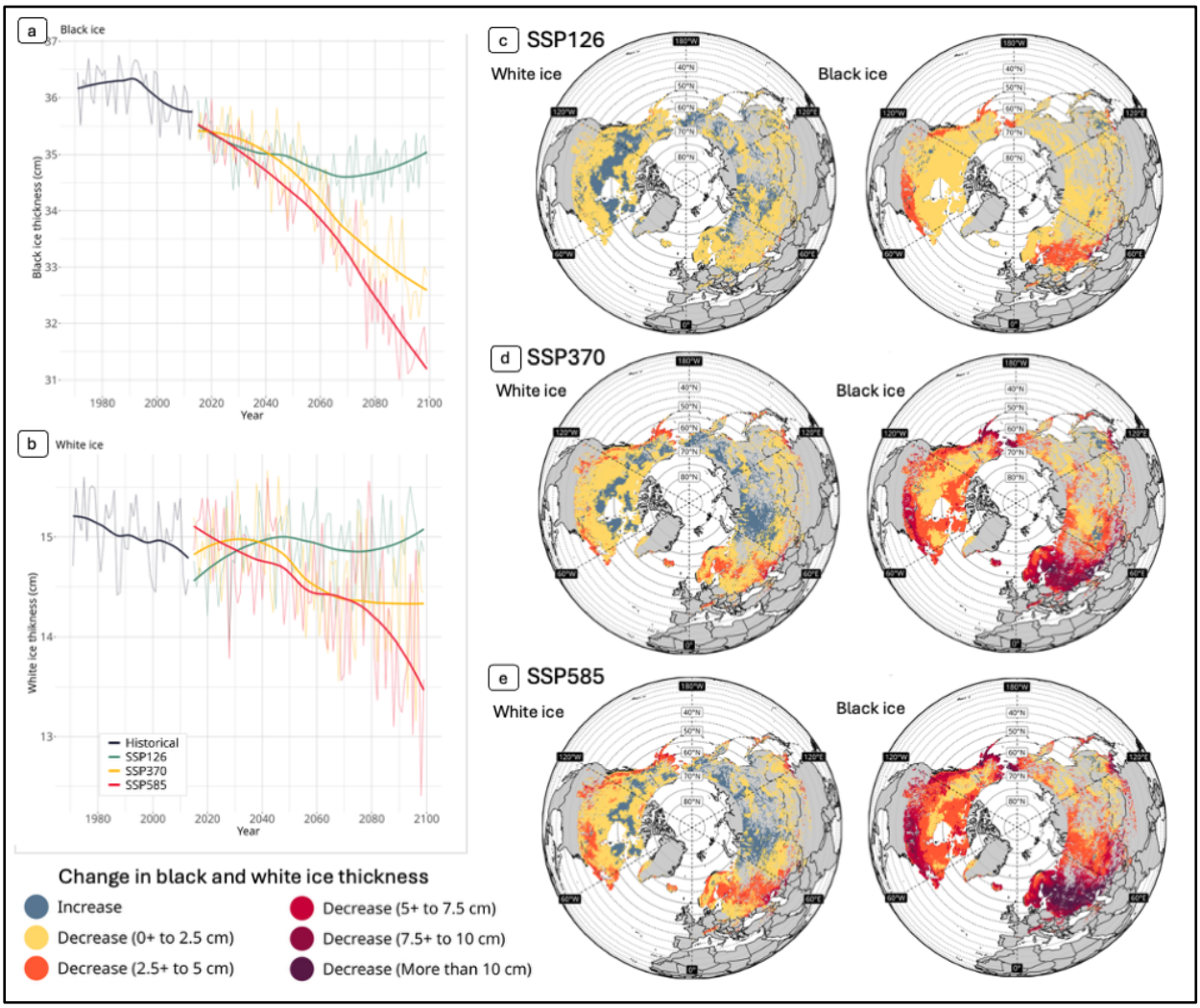


Figure 1: Annual average of a) black ice thickness and b) white ice thickness for historical (1971 - 2013) and forecasted future (2015 - 2099) SSP scenarios for 1.12 million lakes. The thinner line depicts the actual mean, while the thicker line depicts the local polynomial regression line from the locally estimated scatterplot smoothing (LOESS). The right panel depicts three polar plots illustrating changes in white and black ice under c) SSP126 scenario, d) SSP370 scenario, and e) SSP585 scenario, comparing the future 30-year average (2070-2099) to the historical 30-year average (1971-2000).

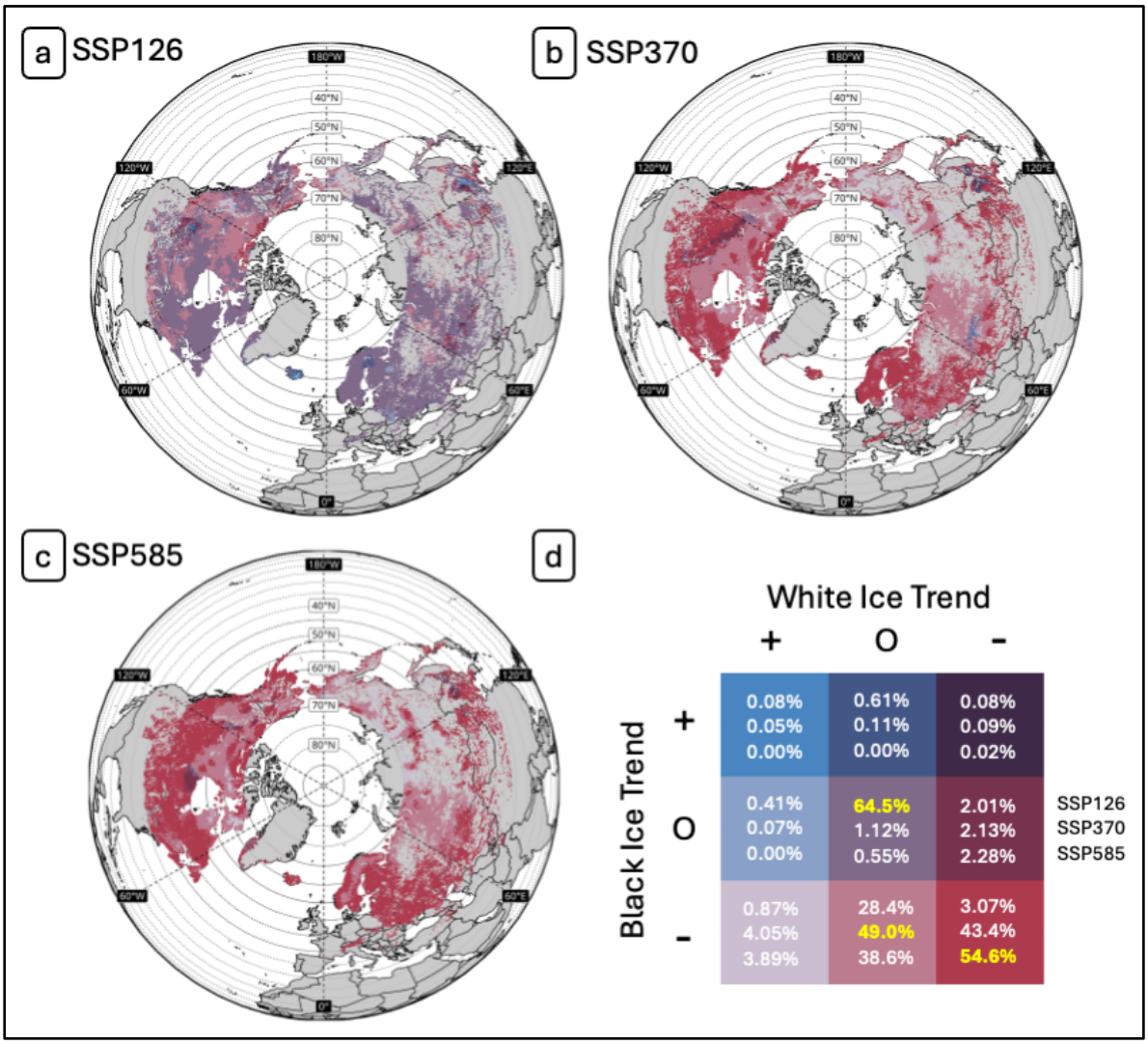


Figure 2: Bivariate color plot for positive (+), negative (-), and non-significant (O) Sens slope trends for white ice and black ice thickness from 2015 to 2099. The nine different colors in the legend illustrate all possible trend combinations of the white ice and black ice pair. Each box presents three percentage values representing the SSP126, SS370, and SSP585 scenarios, which describe the proportion of projected lakes that fall under each trend combination pair. The highlighted yellow values indicate the pair with the maximum percentage from each scenario.

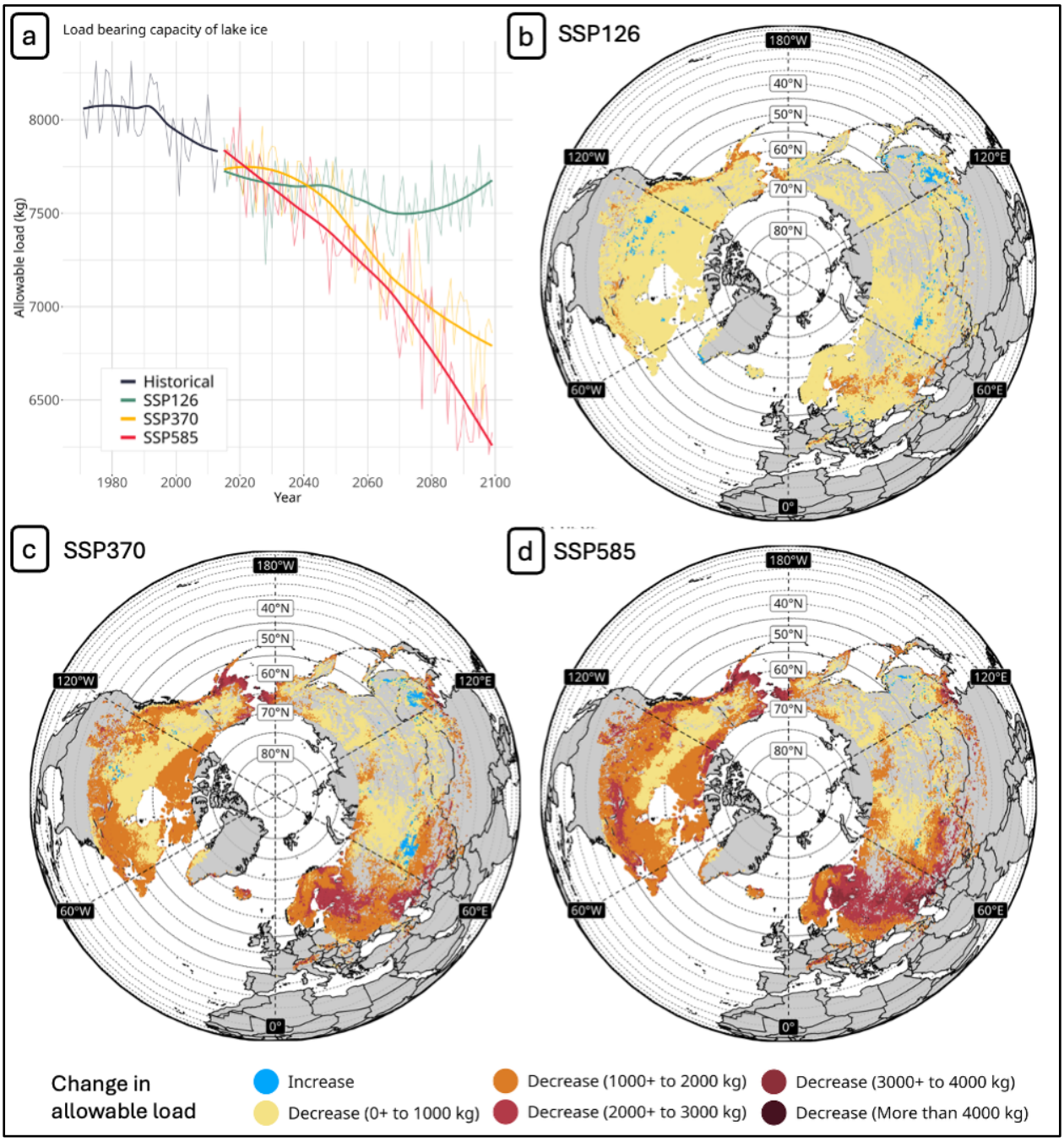


Figure 3: a) Yearly average changes in the load-bearing capacity of lake ice across the Northern Hemisphere. The thinner line represents the actual mean, while the thicker line illustrates the local polynomial regression line from the locally estimated scatterplot smoothing (LOESS). Polar plots of load capacity changes for b) SSP126 scenario, c) SSP370 scenario, and d) SSP585 scenario, over the future 30-year average (2070-2099) compared to the historical 30-year average (1971-2000).

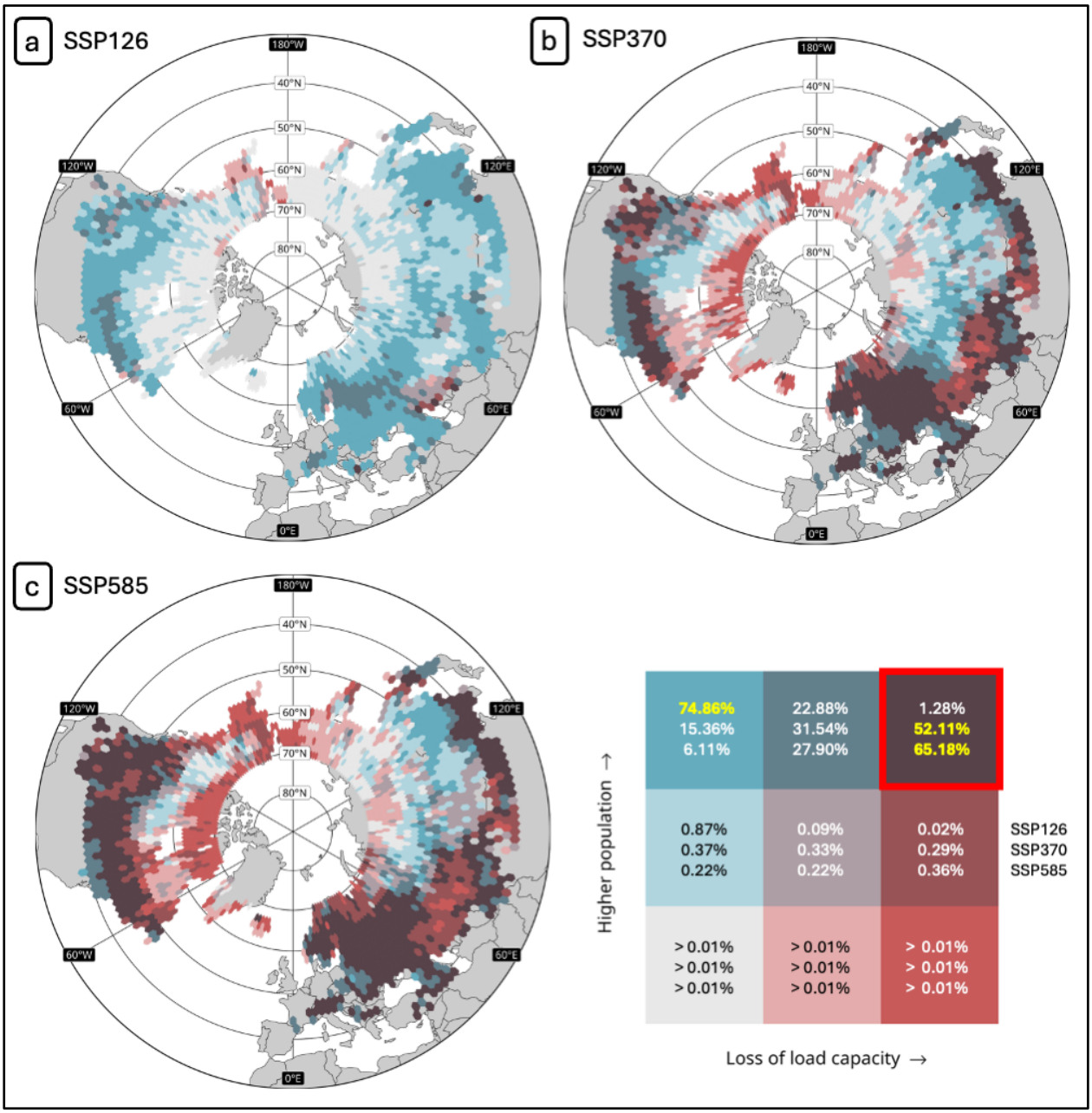


Figure 4: Bivariate color plot for projected population and loss of load-bearing capacity of lakes over the period 2070-2100. The nine color blocks represent the combination of three equal quantiles from the population and the loss of load-bearing capacity (see method section for more detail). The highlighted red box represents high-risk areas where both population and change in ice load-bearing capacity are high. The numbers inside each color section indicate the percentage of the population projected to be in that group between 2070 and 2100 for the specific SSP

scenario. The highlighted yellow values indicate the maximum percentage of the population within a single group in each scenario.

Chapter 4: Elucidating the extent of the influence of land cover on ice phenology across lakes in the northern contiguous United States: Implications for ecosystem management

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Author's Contributions

AB, KV, and SS conceived the research ideas and designed the study. AB developed the methodology, conducted the investigation, performed validation and formal analyses, curated the data, and produced the visualizations. AB and SS contributed resources. KV and SS provided supervision, SS managed project administration, and secured funding. AB and KV wrote the original draft, and AB, SS, and FF participated in the review and editing. All authors contributed to successive drafts and approved the final manuscript for publication.

Summary

Climate change is driving global declines in lake ice cover. Although the influence of large-scale meteorological drivers on ice phenology is well established, the extent to which local and regional landscape characteristics modulate patterns of ice loss remains insufficiently understood. This study analyzes *in situ* ice phenology records (ice-on and ice-off dates) from 3,123 lakes, averaging 16 years of data across five northern U.S. states, to assess the effects of land-cover type (developed, planted-cultivated, and forested) and anthropogenic stressors, including road density, population, nightlight intensity, and the presence of power plants and water treatment plants, on ice phenology at regional scales. At the regional scale, lakes situated within highly urbanized landscapes exhibit the greatest variability in ice phenology (standard deviation of 15.6 ± 2.06 days for ice-on and 15.12 ± 2.22 days for ice-off dates), compared to lakes in forested landscapes, which display the least variability (10.05 ± 2.68 days for ice-on and 11.46 ± 5.93 days for ice-off dates). Similarly, lakes in highly urbanized landscapes show the largest trends of ice loss (a delay of 5.94 ± 5.83 days per decade for ice-on dates and 3.16 ± 1.98 days per decade for ice-off dates), in contrast to lakes in forested landscapes (2.03 ± 3.54 days per decade delay in ice-on dates and an advance of 1.79 ± 3.33 days per decade for ice-off dates). In contrast, models built at the local scale with lake-specific drivers such as meteorology (temperature, precipitation, and cloud cover), lake morphology (area, shoreline length, shoreline complexity), and adjacent land cover (fraction of developed, planted-cultivated, and forested land cover) indicate an overwhelming influence of meteorological drivers on ice phenology, with surrounding land cover and morphology exerting minimal influence. These findings demonstrate that landscape characteristics shape broad spatial patterns of lake ice vulnerability, while climate forcing constrains outcomes at the level of individual lakes. This understanding clarifies the limitations of local management actions and underscores the necessity of broad-scale climate mitigation to address ongoing losses of lake ice cover.

Introduction

Lake ice is critically important to northern ecosystems and communities, supporting ecological systems, economic activities, and cultural and recreational practices (Barrette et al., 2022; Ford et al., 2023; Hampton et al., 2024; Knoll et al., 2019; Magnuson & Lathrop, 2014). Consequently, the loss of lake ice presents significant challenges for communities that depend on reliable lake ice during winter (Filazzola et al., 2024; Hampton et al., 2024). Over the past century, lake ice phenology (ice-on and ice-off dates) has been rapidly changing across the Northern Hemisphere, with widespread shifts toward later freeze-up, earlier break-up, and shorter ice-cover duration (Benson et al., 2012; Magnuson et al., 2000; Newton & Mullan, 2021; Sharma, Richardson, et al., 2021). Climate projections indicate that these trends will persist or intensify, with lakes expected to lose an additional 10-80 days of ice cover by the end of the century (Basu et al., 2024; Grant et al., 2021; Huang et al., 2022; Wang et al., 2022).

Although ice cover has declined in many lakes across the Northern Hemisphere, patterns in ice phenological changes are highly spatially and temporally heterogeneous. For example, an analysis of 1213 lakes across Minnesota spanning 74 years (1949–2022) revealed that 10-20% of lakes exhibited phenological trends that differed from statewide patterns (Walsh et al., 2025). Previous research has largely attributed variability in lake ice phenology to differences in meteorological conditions and lake morphology, both of which regulate heat storage and energy exchange between lakes and the surrounding atmosphere (Brown & Duguay, 2010; Sharma, Blagrave, Filazzola, et al., 2020). Ice-on and ice-off timing have been linked to local, regional, and global meteorological drivers, including air temperature, precipitation, wind speed, cloud cover, and solar radiation (Brown & Duguay, 2010; Kirillin et al., 2012), as well as large-scale climate oscillations (Ghanbari et al., 2009; Imrit & Sharma, 2021; Livingstone, 2000; Livingstone et al., 2010). Lake morphological characteristics, such as depth and surface area, further regulate thermal inertia and energy exchange (Arp et al., 2016; Brown & Duguay, 2010; Higgins et al., 2021), thereby influencing the timing and decay of lake ice (Dibike et al., 2024; Sabás et al., 2024). While these meteorological and morphological drivers are well documented, empirical evidence concerning the relationship between lake ice and the surrounding landscape is limited.

Lakes are embedded in divergent landscapes that differ in land cover composition, human activity, and energy balance, suggesting that regional landscape types may play an important role in shaping lake ice phenology. Existing research alludes to urbanization (Magnuson et al., 2000), human development (Sharma et al., 2016), and industrial structures, such as power plants (Sharma et al., 2013), contributing to accelerated ice loss. However, the comparative influence of broader land cover types, including urban, agricultural, and forested areas, on lake ice phenology has not been systematically investigated. As a result, it remains unclear whether lakes situated within different landscape types exhibit distinct ice phenology patterns, limiting our ability to generalize lake ice responses to climate forcing across regions.

At finer spatial scales, the surrounding landscape may influence ice phenology indirectly by modifying near-surface meteorological conditions that govern heat exchange between the atmosphere and the lake (Deng et al., 2013; Mahmood et al., 2014; Pongratz et al., 2021). Changes in land cover can modify surface albedo, surface roughness, and the partitioning of energy between heat and moisture, thereby affecting near-surface temperature and humidity (Bonan, 2008; Pielke Sr. et al., 2011). Urban environments, for example, replace vegetation with impervious surfaces that retain heat, reducing evaporation and resulting in elevated temperatures in built-up spaces (Oke, 1982; Oke et al., 2017). This urban heat effect is further amplified by anthropogenic heat generated by population density, transportation networks, and industrial operations (Chrysoulakis & Grimmond, 2016; Khan & Simpson, 2001; Lu et al., 2017, 2024). In contrast, agricultural areas may promote localized cooling through enhanced evapotranspiration associated with irrigation and land management practices (Bonfils & Lobell, 2007; Kueppers et al., 2007). Additionally, forested regions exert competing biophysical processes, with increased evapotranspiration generally promoting cooling, while reduced albedo (particularly when forests obscure snow) can lead to warming (Bonan, 2008). Together, these processes suggest that land cover may influence lake ice dynamics both directly and indirectly, interacting with meteorological forcing and lake morphology to shape ice phenology outcomes.

Although numerous studies have linked the long-term declines in lake ice cover to human activity and climate change (Grant et al., 2021; Huang et al., 2022; Magnuson et al., 2000; Sharma et al., 2016), attributing observed changes in ice phenology to regional or local climate factors remains challenging. Uncertainty introduced through the downscaling of global climate

models (Lafferty & Sriver, 2023; Wootten et al., 2017) underscores the need to better understand how landscape characteristics interact with meteorological conditions at spatial scales. Since land and atmosphere interactions are inherently scale dependent (Perugini et al., 2017), evaluating both regional landscape and local land cover effects is essential for understanding the drivers of lake ice variability. This understanding also helps clarify the extent to which local land management practices may influence ice phenology and whether such actions have the potential to mitigate lake ice vulnerability. In this study, we evaluate the role of landscape context in shaping lake ice phenology. At the regional scale, we characterize the landscape types in which lakes are situated and assess whether these landscapes exhibit distinct patterns and trends in ice-on and ice-off dates. At the local scale, we examined how a surrounding land cover influences a specific lake's ice cover duration relative to its meteorological and lake-morphological drivers, thereby clarifying the limits of local management actions. Specifically, we address the following questions: 1) Do trends in ice-on and ice-off date differ by landscape type? 2) What is the relative influence of local land cover, meteorological, and lake morphological factors on ice cover duration?

Methods

1. Data acquisition

Lake ice phenology records for 3,123 lakes were obtained from the Community Lake Ice Collaboration (CLIC) network (Sharma et al., 2023) and the Minnesota Lake Ice Phenology databases (Walsh et al., 2025). These records cover an average of 16 years across five U.S. states: Minnesota, Wisconsin, New York, Maine, and Michigan. In total, 35,467 ice-on and 45,111 ice-off records were compiled, spanning the period from 1843 to 2025.

Land-cover data were acquired from the National Land Cover Database (NLCD) Collection (U.S. Geological Survey, 2024), which provides an annual 30-meter-resolution time series from 1985 to 2024 across 16 land-cover categories in the United States. Furthermore, monthly 2-meter mean air temperature (°C), precipitation (mm/month), and mean cloud cover (%) data were obtained from the Climatic Research Unit Time-Series (CRU-TS) database (Harris et al., 2020), which offers global gridded meteorological data at 0.5° spatial and monthly temporal resolution from 1901 to 2024. Lake morphological characteristics, including shoreline length (km), lake surface area (km^2), and shoreline development factor (the ratio of shoreline

length to the circumference of a circle with the same area as the lake) were obtained from the LAGOS-US database (Rodriguez et al., 2023), which includes lakes in the United States with a surface area of at least 4 hectares.

Human pressures on land, resulting from multiple interacting factors, were summarized using two composite indices. First, the human modification index, which covers 1990 to 2017, integrates land cover change, infrastructure development, and pollution (Theobald et al., 2020). Second is the annual global terrestrial Human Footprint index, which combines variables representing human pressure such as roads, waterways, population density, nighttime light, and land cover (Mu et al., 2022). This dataset provides a 1 km global time series of Human Footprint maps from 2000 to 2018. Individual proxies for anthropogenic stressors were also incorporated, including population data from Liu et al. (2024), a global gridded dataset with annual population estimates from 1990 to 2020 at 30 arc-second resolution, and nighttime light data from Li et al. (2025), which provide a yearly global time series at 30 arc-second resolution from 1992 to 2024. Moreover, we compiled several infrastructure datasets. These included global wastewater treatment plant discharge volumes (m^3/day) and facility locations from the HydroWASTE project (Ehalt Macedo et al., 2022), as well as global road density data (m/km^2) from the Global Roads Inventory Project (GRIP; Meijer et al., 2018) at a resolution of 5 arc-minutes. In addition, locations and electricity generation capacities (MW) of renewable and non-renewable power plants were obtained from the World Resources Institute's global power plant database (Byers et al., 2018).

2. Data analysis

Ice phenology patterns were examined at both regional and local scales using two analytical approaches, each with distinct lake-specific inclusion and exclusion criteria (Figure 1). For the regional-scale analysis addressing the first research question (Do trends in ice-on and ice-off date differ by landscape type?), lakes were required to have sufficiently long and complete time series to determine lake-specific phenology variability and trends. Only lakes meeting these criteria were included in the regional-scale downstream analysis. In contrast, the local scale analysis addresses the second research question (What is the relative influence of local land cover, meteorological, and lake morphological factors on ice cover duration?) included all available lake ice phenology measurements that could be spatially matched to shoreline polygon

data from the LAGOS-US database (Rodriguez et al., 2023), provided that corresponding lake-surrounding land cover and meteorological data were available for model development.

2.1. Regional-scale Analysis: Do trends in ice-on and ice-off date differ by landscape type?

2.1.1. Defining landscape types by characterizing spatial segments of the study region

To capture spatial heterogeneity in landscape characteristics, the study region was partitioned into hexagonal spatial polygons with a width of 150 km using the "sf" package (Pebesma & Bivand, 2023), resulting in 101 hexagonal subregions. For each hexagon, the percentages of each land-cover type were calculated, along with the total population for all available years. For wastewater treatment plants and power plants located within each hexagon, total treated wastewater volume and total renewable and non-renewable power generation capacity were calculated. Spatially average values of road density, nighttime light intensity, human modification, and human footprint were also calculated for each polygon. For variables with annual temporal data, including land cover, population, nightlight, human land modifications, and human footprint, spatially averaged values (or percentages, for land cover) were calculated per hexagon and then averaged across their respective time series. To facilitate the identification of distinct landscape types, we aggregated the original 16 land cover categories into 8 broader categories based on class similarity (U.S. Geological Survey, 2024). These new groups include: water (open water, perennial ice/snow), developed (developed open space, low, medium, and high intensity), barren (barren land- rock/sand/clay), forest (deciduous, evergreen, and mixed forest), shrubland (shrub/scrub), herbaceous (grassland/herbaceous), planted/cultivated (pasture/hay and cultivated crops), and wetlands (woody wetlands and emergent herbaceous wetlands). Because barren, shrub, and herbaceous land-cover types accounted for 1% or less of the study region, these categories were excluded from subsequent analysis. Water and wetland categories were also removed to isolate land-based processes most relevant to lake ice phenology, leading to only the developed, planted-cultivated, and forested land cover categories for the downstream analysis.

2.1.2. Determining regional landscape clusters and their defining characteristics

To group lakes by landscape classification, we first characterized the surrounding landscape of each lake using polygon level variables describing land cover, human population,

and infrastructure density. Landscape types were then identified using k-means clustering with Euclidean distance applied to these variables, all of which were scaled prior to clustering. The optimal number of clusters was determined by the elbow method (Kaufman, 2005), which evaluates the total within-cluster sum of squares (WSS). This procedure was implemented using the "factoextra" package (Kassambara & Mundt, 2020). Following cluster identification, principal component analysis (PCA) was conducted to examine which land cover types contributed most strongly to cluster separation. To aid interpretation, cluster-level profiles were visualized by normalizing variables within each cluster to a 0-1 scale and presenting them as radial (radar) plots.

2.1.3. Metrics used to characterize changes in regional lake ice phenology

Lakes were included if both ice-on and ice-off dates were available for at least 10 years and if missing data did not exceed 15% of the time series. Missing ice-on and ice-off observations were imputed using the average ice-on or ice-off date of each lake's ice record (Sharma, Blagrave, et al., 2021). This filtering yielded 27,017 ice-on and 27,378 ice-off observations from 1,097 lakes. The land areas encompassing these 1,097 lakes were subsequently used to characterize regional landscape patterns. Ice-on and ice-off dates for the 1,097 lakes included in the regional-scale analysis were converted to day-of-year (DOY) values using September 1 as the reference date. For each lake, standard deviations and Sen's slopes were calculated for the ice-on and ice-off DOY to assess variability and temporal trends in ice phenology using the "zyp" package (Bronaugh & Schoeneberg, 2023). Although paired changes in ice-on and ice-off dates across years provide insight into the seasonal consistency of lake ice cover, direct comparison across lakes is challenging due to large differences in baseline phenology (e.g., two adjacent lakes may exhibit substantial variation in ice-cover duration and phenological patterns due to differences in size). To facilitate comparison among lakes and across landscape clusters, the midpoint between ice-on and ice-off DOY was calculated for each year and used as a proxy for the annual timing of the ice season. Sen's slope of this midpoint DOY was then calculated for each lake to quantify long-term shifts in ice season timing.

Differences in ice phenology variability and trends among landscape clusters were assessed using Kruskal-Wallis tests applied to lake-level standard deviations and Sen's slopes for ice-on, ice-off, and mid-season DOY. When the global Kruskal-Wallis test indicated significant

differences, pairwise post hoc comparisons between clusters were conducted using Dunn's test with a Benjamini-Hochberg adjustment for multiple comparisons. For each metric, the global Kruskal-Wallis p-value and the adjusted pairwise p-values were reported.

2.2. Local Scale Analysis: What is the relative influence of local land cover, meteorological, and lake morphological factors on ice cover duration?

2.2.1. Obtaining local scale predictors of lake ice duration

Local-scale drivers of ice phenology were derived by linking ice phenology data to lake-specific land cover, meteorological, and morphological data. Lake-area polygons were extracted from the LAGOS-US lake database (Rodriguez et al., 2023), and ice phenology measurement locations were retained if they fell within the corresponding lake polygon or within 10 meters of the shoreline. This method accounted for minor discrepancies between mapped shorelines and sampling locations. To obtain lake surrounding landcover information, a 10 km buffer was generated around each lake shoreline using the lake polygons (Hillman & Nielsen, 2025), and the proportional coverage of developed, planted-cultivated, and forested land was calculated within each buffer. Other land-cover categories were excluded to maintain consistency with the regional-scale analyses. Temperature, precipitation, and cloud cover were obtained from the CRU-TS database (Harris et al., 2020) and averaged over fall (SON), winter (DJF), and spring (MAM) for grid cells encompassing each ice phenology sampling location. The analysis was constrained to the September-May period to align with key drivers of ice phenology. Fall conditions are a critical predictor of ice-on (Oleksy & Richardson, 2024; Sabás et al., 2024), and spring air temperatures drive the timing of ice-off (Lopez et al., 2019; Palecki & Barry, 1986). Further, our observational records for ice duration extend from November through early May. Lake morphological variables, including shoreline length, surface area, and shoreline development factor, were obtained from the LAGOS-US lake database (Rodriguez et al., 2023) and incorporated as predictors in the lake ice duration model. Only years with both ice-on and ice-off records were retained to calculate ice cover duration, yielding 22,783 ice-duration measurements from 1,803 lakes spanning 1985 to 2023.

2.2.2. Random forest model for local scale ice cover duration

A random forest model was used to ascertain the relative importance of climate, lake morphology, and land cover on ice cover duration. Model performance was evaluated using a 10-fold spatiotemporal cross-validation implemented with the “mlr3spatiotempcv” package (Schratz & Becker, 2024). The random forest model was developed with the “ranger” R package (Wright & Ziegler, 2017), and hyperparameter optimization was performed with the “mlr3verse” package (Lang & Schratz, 2023). Partial dependence for all nine predictors (temperature, precipitation, cloud cover, developed, planted-cultivated, and forest land, shoreline length, shoreline development, and lake area) was analyzed using the “pdp” package (Greenwell, 2017), and permutation variable importance was assessed using 50 random permutations with the “DALEX” package (Biecek, 2018).

Results

First, we characterized regional spatial segments of the study region defined by landscape types and human pressure. Based on the elbow method, four clusters (k=4) were identified among the 101 hexagonal subregions, as additional clusters resulted in only marginal reductions in within-cluster sum of squares (Supplementary Figure 1). Each cluster demonstrates distinct characteristics (Figure 2a). Cluster 1 was characterized by high levels of urban development, population density, and infrastructure. Cluster 2 exhibited moderate development and intermediate anthropogenic stressors. Cluster 3 was dominated by cultivated land and agricultural activity, while cluster 4 consisted primarily of a forested landscape with minimal infrastructure.

Principal component analysis (PCA) supported these classifications (Figure 2b). The first two principal components accounted for 76.7% of the variation in landscape characteristics, with PCA axis 1 explaining 55.1% and PCA axis 2 explaining an additional 21.6%. PCA axis 1 reflected a gradient of urbanized to forested regions, while axis 2 distinguished cultivated landscapes from densely developed areas. The spatial distribution of clusters corresponded to recognizable geographic regions (Figure 2c), with urban clusters centered around metropolitan areas, agricultural clusters spanning farmed regions, and forested clusters located primarily in northern areas.

1. Do trends in ice-on and ice-off date differ by landscape type?

Interannual variability in lake ice-on and ice-off dates differed significantly across the distinct clusters (p-values < 0.001; Figure 3a). Lakes located in highly urbanized cluster 1 exhibited the greatest year-to-year variability, with mean ice-on and ice-off deviations of 15.6 ± 2.06 days and 15.12 ± 2.22 days, respectively. In contrast, forest-dominated cluster 4 displayed the lowest variability across both metrics, with ice-on varying by 10.05 ± 2.68 days and ice-off by 11.46 ± 5.93 days on average. Cluster 2 and 3 displayed moderate levels of variability. Lakes in moderately developed cluster 2 had the second highest variability (11.81 ± 2.98 days for ice-on and 13.44 ± 4.81 for ice-off), followed closely by cluster 3, representing plant-cultivated land (10.9 ± 4.19 days for ice-on and 12.52 ± 5.09 for ice-off). Dunn's post hoc comparisons confirmed that all pairwise differences among these clusters were statistically significant.

Long-term trends in ice phenology also differed significantly among the four landscape clusters (Figure 3b). While all clusters exhibited a trend towards later ice-on, the magnitude of change varied significantly (Kruskal–Wallis, p = 0.0033). The strongest delays in ice-on occurred in the highly urbanized cluster 1, where ice-on was delayed by an average of 5.94 ± 5.83 days per decade. In contrast, clusters 2 (1.98 ± 3.72 days per decade), 3 (1.91 ± 3.44 days per decade), and 4 (2.03 ± 3.54 days per decade) showed more modest delays at approximately 2 days per decade, with no significant differences among these three clusters.

Ice-off trends demonstrated even greater divergence among clusters (Kruskal–Wallis p < 0.001; Figure 3b). Lakes in cluster 1 exhibited the strongest shift towards later ice-off dates, with ice-off occurring 3.16 ± 1.98 days later per decade on average. Clusters 2 (0.13 ± 3.78 days per decade) and 3 (-0.33 ± 2.75 days per decade) showed little directional change over time, with median slopes of zero. In contrast, lakes in the forest-dominated cluster 4 tended toward earlier ice-off, advancing by 1.79 ± 3.33 days per decade on average. Dunn's post hoc tests confirmed that pairwise differences between the forested cluster and the more developed clusters were highly significant.

Trends in the midpoint of the ice season differed significantly among clusters (Kruskal–Wallis p < 0.001; Figure 3c). Cluster 1 exhibited the largest shift, with the mid-season delayed by an average of 4.17 ± 3.61 days per decade. Smaller positive shifts were observed in clusters 2 (0.96 ± 2.71 days per decade) and 3 (0.73 ± 2.15 days per decade), while cluster 4 showed no consistent directional change in the midpoint of the ice season (-0.05 ± 2.5 days per decade).

Post hoc Dunn tests confirmed that cluster 1 differed significantly from all other clusters. In contrast, clusters 2 and 3 were not statistically distinguishable from one another (ns), though both differed significantly from cluster 4.

2. What is the relative influence of local land cover, meteorological, and lake morphological factors on ice cover duration?

The random forest model predicting ice-cover duration based on climate, lake morphology, and land cover explained 76% of the variation in the data, with a Mean Absolute Error (MAE) of 9.5 days and a Root Mean Squared Error (RMSE) of 13.8 days (Supplementary Figure 2). Permutation-based variable importance analysis identified that meteorological factors predominantly determined model performance for ice duration (Figure 4a,b). Among all predictors, average air temperature emerged as the strongest predictor; permuting this variable produced a substantially larger increase in RMSE (median loss of ~18–20 after 50 permutations) than any other predictor variable (Figure 4a). Precipitation, developed land, and cloud cover contributed modestly to model performance, each increasing RMSE by approximately 1-3 days when removed. In contrast, forest cover, cultivated land, and morphometric metrics such as lake area, shoreline length, and shoreline development contributed only minor incremental improvements. Grouping predictors into meteorology, landcover, and morphology further supported this pattern (Figure 4b). Meteorological variables accounted for nearly all predictive power, with land cover and morphological variables contributing only marginal explanatory value.

Partial dependence plots revealed non-linear relationships amongst the predictor variables (Figure 4c). Ice duration declined steeply with increasing average air temperature. Notably, an increase in air temperatures between 0°C and 2°C was associated with a decline in ice duration of 12-15 days. Ice duration also declined with increasing precipitation. For cloud cover, ice duration remained relatively stable, but decreased sharply when cloud cover reached over 70%. Partial dependence plots of land cover variables revealed minor effects on ice duration compared to meteorological variables. Ice duration decreased by 5-6 days as development increased. Notably, increasing the proportion of developed land was associated with a rapid initial decline in ice duration, particularly at low levels of development. Partial dependence plots also showed non-linear relationships between lake morphology and ice duration. Ice duration declined with

increasing lake size and shoreline length, while the shoreline development factor exhibited a weak, non-monotonic pattern.

Discussion

This study aimed to illuminate how land cover characteristics influence lake ice phenology at both regional and local scales owing to the large spatial heterogeneity evident in ice phenological records (Basu et al., 2024). While previous research on lake ice drivers has primarily focused on meteorological and morphological factors (Brown & Duguay, 2010; Higgins et al., 2021; Smits et al., 2021), the role of land in lake ice remains largely unexamined. Our findings reveal that ice phenology patterns differ substantially among landscape types at the regional level. Lakes situated in highly urbanized landscapes exhibit the greatest interannual variability and the most pronounced long-term trends, followed by those in moderately developed and agricultural landscapes. In contrast, forested landscapes showed the lowest variability and weaker directional change. At the individual lake scale, meteorological variables emerged as the primary determinants of lake ice cover duration, whereas lake morphology and land cover characteristics, though comparable to one another in magnitude, exerted considerably less influence. Management strategies aimed at preserving land cover, in concert with limiting greenhouse gas emissions, offer opportunities to preserve lake ice cover for lakes across landscapes at high threat of losing ice in the coming decades.

1. Do trends in ice-on and ice-off date differ by landscape type?

Lake ice phenology differed systematically across dominant regional land-cover types, with the variability and rate of ice loss increasing from forest-dominated to urbanized landscapes. The pronounced variability and accelerated ice loss observed in human-modified landscapes arise from the complex interaction between anthropogenic heat inputs and the inherent sensitivity of ice formation near climatic thresholds. Urban environments are characterized by impervious surfaces that absorb heat and release it slowly into the atmosphere (Arnfield, 2003; Oke, 1982), contributing to elevated local temperatures. This effect is further amplified by anthropogenic heat from buildings, transportation, and industrial activity, which collectively raise near-surface air temperatures in and around metropolitan areas (Lu et al., 2024; Sailor, 2011). Collectively, these processes intensify urban heat island effects (Arnfield, 2003;

Oke, 1982), thereby increasing the frequency of marginal winter conditions during which air temperatures fluctuate near the freezing point. Under such conditions, lake ice phenology becomes highly sensitive to small temperature fluctuations near 0°C (Brown & Duguay, 2010; Leppäranta, 2023; Weyhenmeyer et al., 2004), rendering these lakes inherently more vulnerable to unstable ice regimes. As winters continue to warm, some lakes will transition toward intermittent ice regimes (Sharma, Blagrave, et al., 2021; Sharma et al., 2019), where moderate fluctuations in large-scale climate drivers and synoptic weather patterns produce increasingly unpredictable ice seasons (Imrit & Sharma, 2021; Livingstone, 2000; Livingstone et al., 2010; Lopez et al., 2019; Richardson et al., 2024). In this way, highly urbanized landscapes may accelerate mean ice loss and amplify year to year variability, making ice cover increasingly difficult to predict.

In contrast, lakes situated in forested landscapes are fundamentally buffered against short-term atmospheric variability. Forested regions exert a moderating influence on near-surface meteorological conditions by regulating surface heat balance, radiation, and near-surface turbulent mixing (Davis et al., 2019; De Frenne et al., 2019; Zellweger et al., 2019). Through these mechanisms, forest cover dampens diurnal temperature fluctuations, lessens extreme events, and limits short-term temperature variability relative to urban or open landscapes (De Frenne et al., 2019; Ge et al., 2022). This climate buffering stabilizes winter conditions near lakes, contributing to reduced variability in freeze and breakup timing. As a result, ice phenology in forested regions may exhibit lower interannual variability, reflecting the role of the surrounding landscape. However, it is important to note that forested regions also occurred farther north in relatively colder areas, where longer freezing periods may be inherently less variable (Richardson et al., 2024). Therefore, the degree of lower variability observed in forested regions may be partly amplified by regional temperature gradients rather than land cover alone.

Taken together, these findings suggest that the observed gradient in the variability and rate of ice loss, from highly urbanized to forest-dominated regions, reflects contrasting landscape-climate interactions that mediate lake sensitivity to warming winters. While the overarching trend towards ice loss is driven by large-scale climate warming, regional land cover appears to modulate the pace and stability of this response. In this context, anthropogenic landscape modifications may not only accelerate ice loss but also increase the unpredictability of

seasonal ice regimes under continued warming. As warming continues, these lakes may be more susceptible to unstable ice regimes, with implications for aquatic ecosystems, winter recreation, safety, and connectivity.

2. What is the relative influence of local land cover, meteorological, and lake morphological factors on ice cover duration?

While regional land-cover types structured differences in ice phenology, local-scale modeling revealed that meteorological forcing overwhelmingly remains the dominant control on ice cover duration within individual lakes. Specifically, air temperature emerged as the primary determinant of ice duration, overwhelmingly outweighing the influence of local land cover composition and lake morphology. This finding is consistent with the fundamental thermal constraint governing lake ice formation, as freeze and breakup processes are tightly regulated by temperatures relative to 0 °C (Blagrave & Sharma, 2023; Brown & Duguay, 2010; Korhonen, 2006; Leppäranta, 2023; Palecki & Barry, 1986; Vavrus et al., 1996). As ice formation and persistence depend on sustained subfreezing conditions, even small warm anomalies can disrupt or shorten the ice seasons as lakes approach this critical threshold. Thus, meteorological variability exerts a direct and immediate influence on ice duration that local landscape characteristics cannot fully offset.

Although land-cover composition can affect near-surface temperatures through established biophysical mechanisms, including albedo, surface roughness, and evapotranspiration (Bonan, 2008; Pielke Sr. et al., 2011), these effects are generally weak relative to regional (Duguay et al., 2006; Weyhenmeyer et al., 2004; Williams et al., 2004) and large-scale atmospheric variability (Imrit & Sharma, 2021; Livingstone, 2000; Livingstone et al., 2010; Lopez et al., 2019). Broad-scale climate patterns often impose consistent temperature anomalies across broad geographic areas, where lakes experience synchronized ice phenology even when local landscapes differ. Consequently, while land cover may induce minor changes in ice duration for certain lakes, dominant meteorological conditions ultimately determine lake ice duration.

Management Implications

Previous research has outlined global strategies for anticipating changes in lake ice through scenario-based projections such as the Shared Socioeconomic Pathways (SSPs) (Basu et al., 2024; Huang et al., 2022). These frameworks assess climate-related risks under alternative socioeconomic, political, and technological trajectories (O'Neill et al., 2017), ranging from sustainability-oriented pathways (Pedde et al., 2019) to fossil-fuel intensive futures (Kriegler et al., 2017). While these frameworks offer strategic guidance for understanding long-term global risk, translating global climate projections into actionable regional management remains challenging due to the scale, complexity, and societal heterogeneity of climate change (Frame et al., 2018; IPCC, 2022; Keohane & Victor, 2011; Ostrom, 2010). By explicitly quantifying how landscape composition modulates lake ice phenology across scales, this study helps bridge the gap between global climate frameworks and local-regional land-use decision making, enabling more targeted strategies that complement broader mitigation efforts.

At the regional scale, increasing anthropogenic pressure on landscapes was associated with greater variability and more rapid changes in ice phenology. Relative to forested landscapes, agricultural and urbanized regions exhibited progressively greater interannual variability in both ice-on and ice-off dates, with the most pronounced changes observed in highly urbanized settings where variability increased by up to 5 days (as indicated by higher median values). Highly urbanized landscapes also experienced a corresponding shift in the timing of the ice season, advancing by approximately 5 days per decade relative to forested regions. These findings indicate that preserving natural landscapes, particularly forested regions, may help stabilize regional ice regimes and enhance predictability. Given the ecological importance of lake ice for ecosystem health (Hampton et al., 2024), regional land-use planning strategies that maintain natural landscapes in sensitive ecoregions may foster a more resilient ice regime while delivering co-benefits through reduced anthropogenic pressures (Grantham et al., 2020; Watson et al., 2018). From a management perspective, regional land use planning and conservation policies that limit further development may serve as a practical adaptation measure that complements broader mitigation

At the local scale, land cover effects on lake ice duration were comparatively modest and strongly context dependent. Among the land cover types examined, development showed the most discernible influence on ice duration. The development of previously undeveloped land by

0-20% reduced ice duration by approximately five days. This pattern suggests that preventing new development in previously undeveloped areas may yield greater benefits than attempting to modify existing urbanized landscapes. In contrast, increasing forest cover did not constantly extend ice duration, and in snow-dominated regions, may even contribute to localized winter warming by reducing surface albedo (Alkama & Cescatti, 2016; Anderson et al., 2011; Betts, 2000; Bonan, 2008). Agricultural land showed weak and inconsistent relationships with ice duration, likely reflecting variability in crop type, soil moisture, residue, snow exposure, and irrigation intensity (Hirsch et al., 2018; Pielke Sr. et al., 2011; Sacks et al., 2009). Collectively, these results suggest that local land management should be viewed as a marginal-preservation strategy that may buffer lakes near thermal thresholds, rather than alternatives to emissions mitigation or regional climate adaptation.

Conclusions

This study demonstrates that the influence of landscape context on ice phenology operates differently across scales. At the regional level, land cover plays a meaningful role in structuring patterns of lake ice phenology, with forested landscapes associated with more stable ice regimes and anthropogenically modified landscapes associated with greater variability and more rapid change. Conservation of forested land cover is therefore expected to reduce variability in regional ice phenology, whereas increasing urbanization or industrialization will exert a destabilizing effect. In contrast, at the local scale, land cover modifications exert comparatively limited influence relative to meteorological forcing. As such, local land-cover interventions should be understood as marginal-preservation strategies for ice loss.

While the analyses presented in this study are correlational and do not establish causality, the observed patterns are consistent with established biophysical mechanisms linking land cover to surface energy balance and near-surface climate. Importantly, the relatively modest influence of local land-cover change on ice duration should not be interpreted as justification for inaction. Reducing near-lake development and limiting anthropogenic heat inputs can offer substantial co-benefits, including improved winter safety (Sharma, Blagrave, Watson, et al., 2020), enhanced habitat protection (Woolway et al., 2022), and better water quality preservation (Hampton et al., 2024). Beyond direct ecological benefits, these actions strengthen governance capacity (Ostrom, 2009; Radinger-Peer et al., 2025), demonstrate feasible responses to climate stressors (Schulze,

2024; Zhang & Xing, 2025), and build public support for broader mitigation strategies (Montfort et al., 2023), thereby informing the policies and investments necessary for sustained mitigation at regional and global scales (Dubash et al., 2022).

Taken together, these findings support a hierarchical framework in which broad-scale climatic forcing governs the fundamental conditions for ice formation and loss, while landscape composition can modulate the magnitude, variability, and spatial expression of these signals. Preserving regional landscape integrity can help stabilize ice regimes, while local land-use decisions can modestly buffer vulnerable systems and generate critical ecological and social co-benefits. However, neither approach substitutes for sustained reductions in greenhouse gas emissions. The persistence of seasonal lake ice ultimately depends on large scale climate trajectories, but the way this loss unfolds across regions can be shaped by human decisions. In this context, lake ice phenology serves as an indicator of broad-scale climate change and a lens for evaluating how multi-level governance can shape ecological resilience in a warming world.

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Figure and Tables

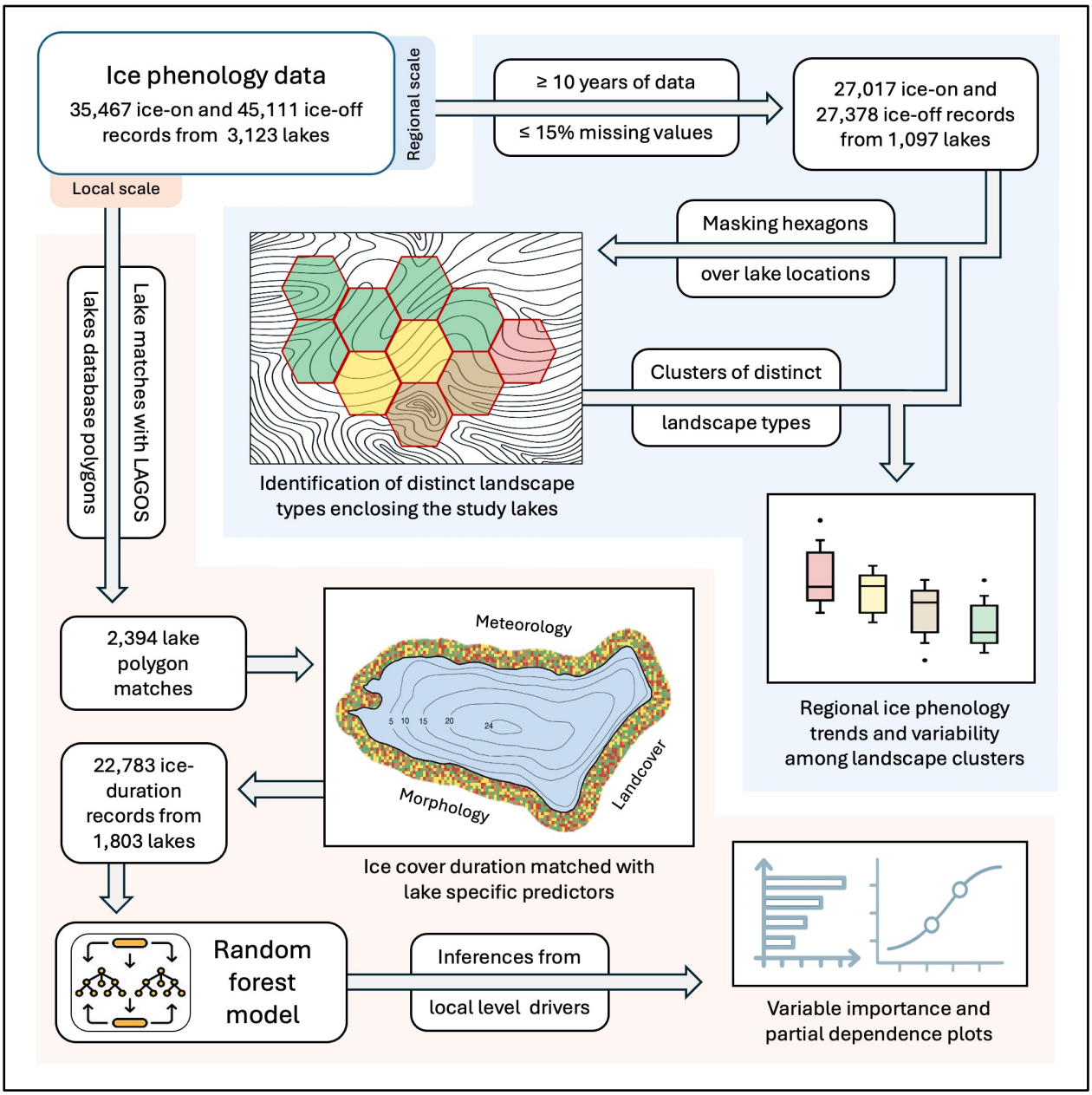


Figure 1: Schematic representation of the analytical steps taken for assessing ice phenology patterns at both regional (blue shaded area) and local (red shaded area) scales.

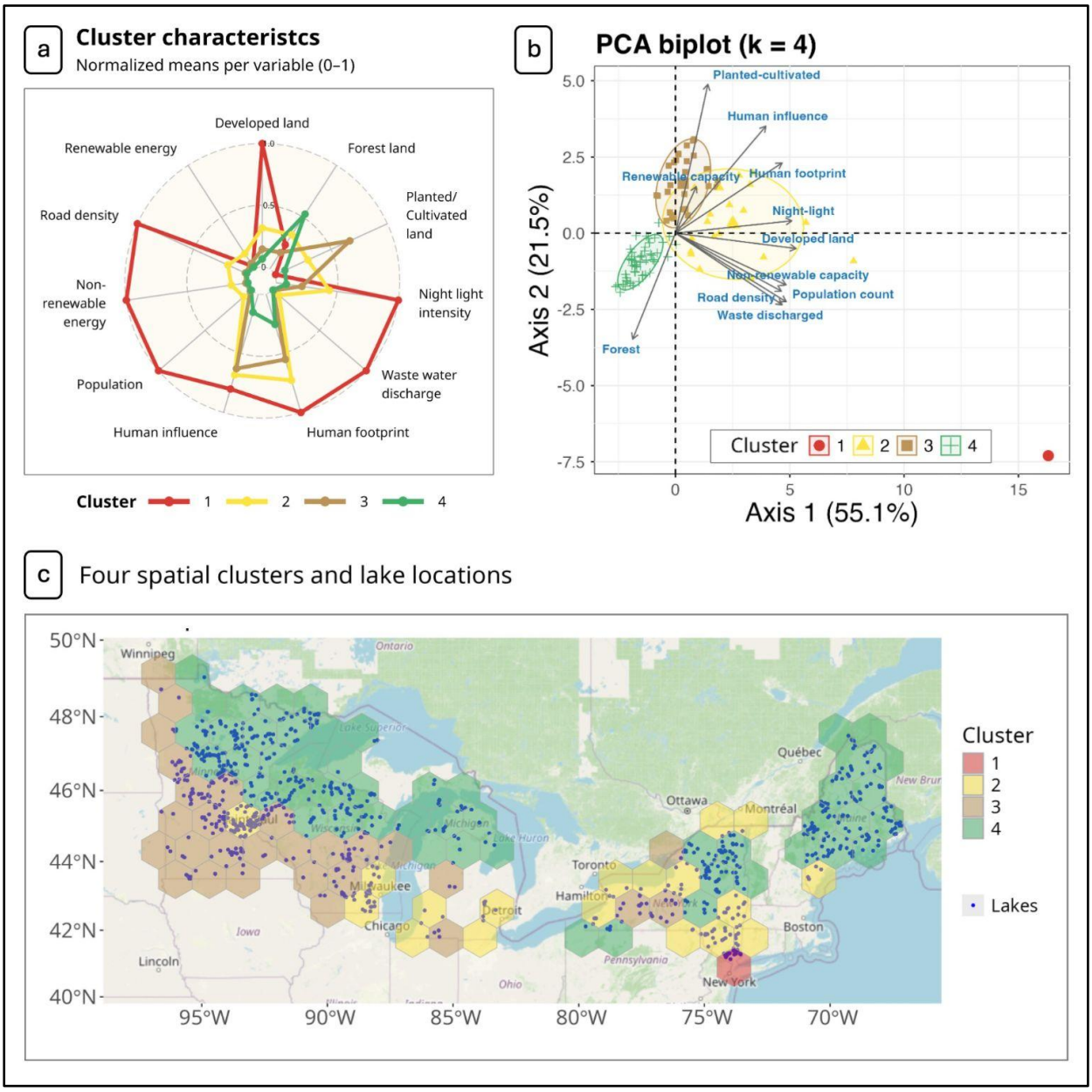


Figure 2: a) Radar plot summarizing the highly urbanized (cluster 1), urbanized (cluster 2), planted/cultivated (cluster 3), and forested (cluster 4) clusters, where lines show cluster means for the normalized indicators. b) A biplot of principal components (PC1 = 55.1%, PC2 = 21.6%) depicting 150 km hexagonal blocks based on human pressures and land cover variables. The points are colored according to k-means clustering (k = 4), with arrows indicating variable loadings. c) Study area map displaying the four k-means clusters assigned to 150 km hexagons across the study region, where blue points represent monitored lake locations.

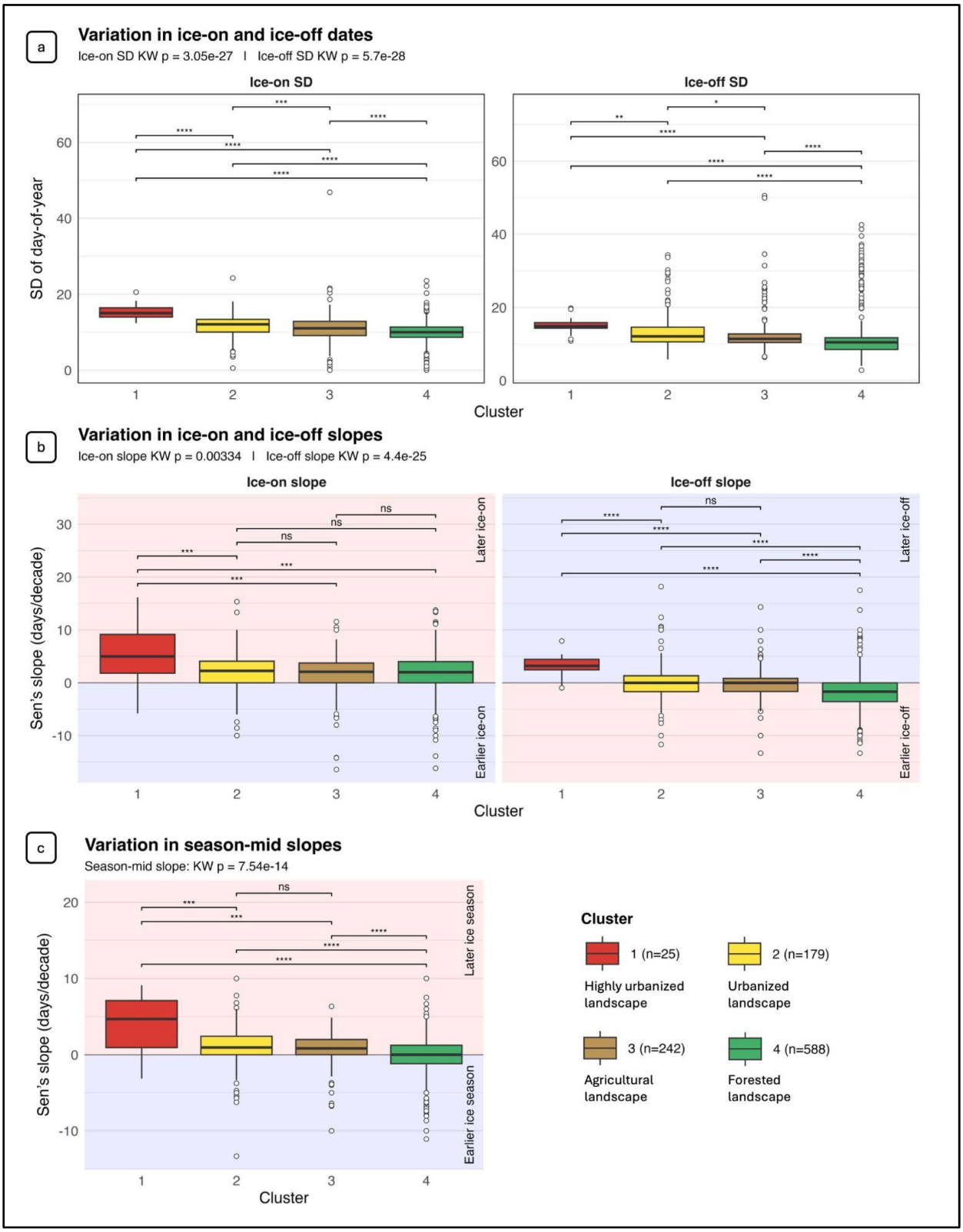


Figure 3: a) Boxplots of interannual variability in ice phenology, quantified as the standard deviation (SD) of day-of-year for ice-on and ice-off dates within each cluster. b) Boxplots of

Sen’s slope trends (days/decade) for ice-on and ice-off dates within each cluster. c) Boxplots of season-mid Sen’s slope trends (days/decade) for the midpoint of the ice season within each cluster. In slope panels, positive slopes indicate a shift toward later timing (red background shading) and negative slopes indicate earlier timing (blue background shading).

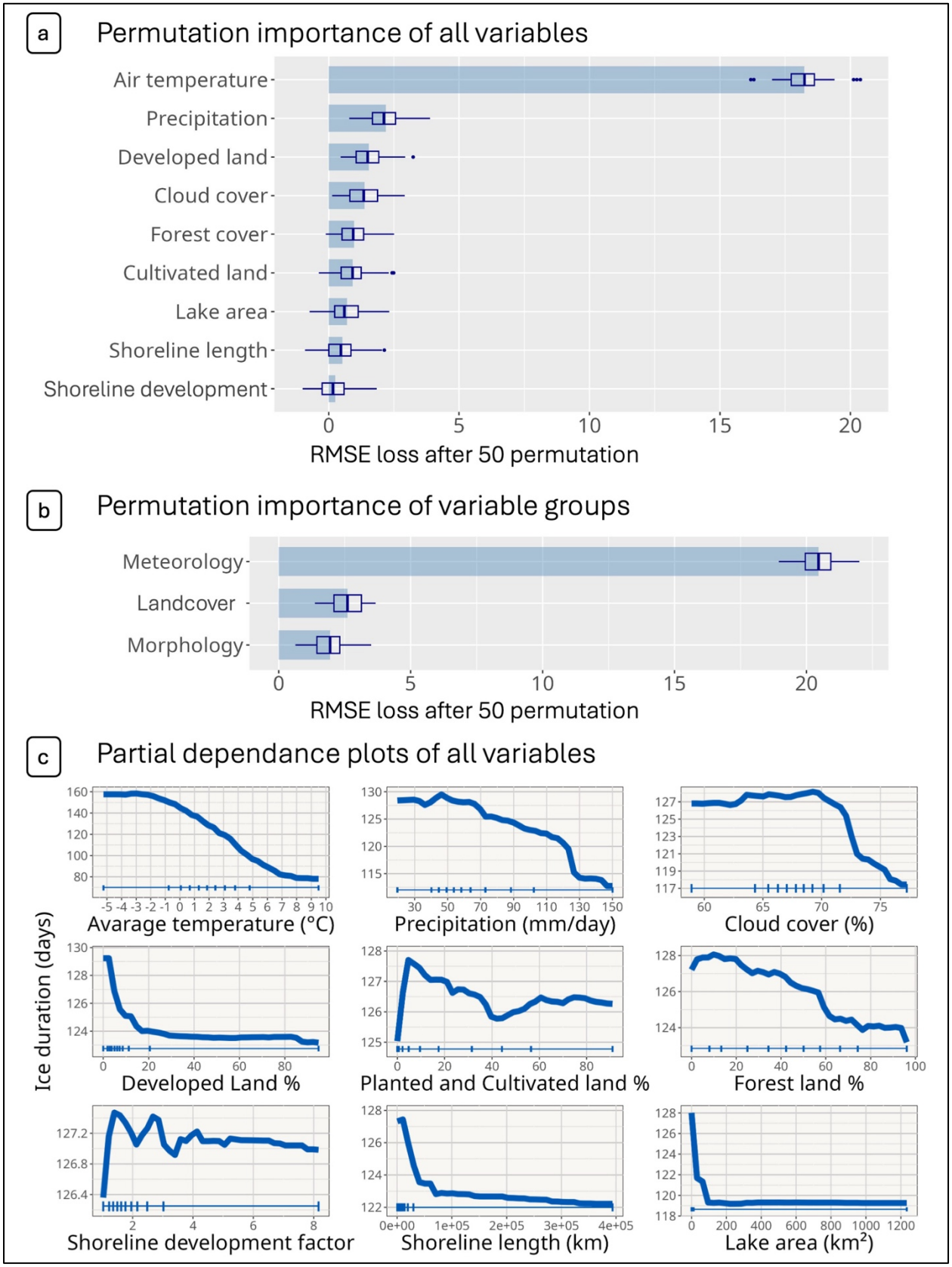


Figure 4: a) Permutation importance plot of all variables used for building the ice duration

model. b) Permutation importance plot of grouped variables (meteorology, landuse, and lake morphology) depicting the importance of each type of variable used in building the ice duration model. c) Partial dependence plots depicting the relationship between the change in individual predictors and ice duration.

Chapter 5: General Conclusion

Lake ice is undergoing rapid changes in response to a warming climate, with considerable ecological, economic, and societal consequences (Hampton et al., 2024; Woolway et al., 2022). Considering lake ice strongly regulates winter conditions and supports a wide range of human activities, understanding how ice regimes are changing is essential for anticipating future impacts on freshwater ecosystems and the communities that depend on them. This thesis examines the future of lake ice across multiple scales by projecting changes in ice phenology (Chapter 2) and ice quality (Chapter 3) across Northern Hemisphere lakes through the end of the 21st century. Furthermore, this thesis assesses the influence of local and regional drivers, particularly those impacted by human activities, to inform targeted interventions at both regional and local scales (Chapter 4). Collectively, these chapters provide new insights into the trajectory of lake ice across the northern hemisphere and highlight opportunities for mitigation and adaptation at global, regional, and local scales.

In Chapter 2 (Basu et al., 2024), I demonstrated that lakes are losing ice cover substantially faster than previously reported, with average rates of ice loss approximately 9 times greater than earlier estimates. Rapid shifts in ice phenology were detected during the 1988–1989 ice season, coinciding with both natural and anthropogenic global climate shifts in the 1980s. This chapter incorporated extensive data with lakes smaller than 1 km^2, thereby integrating the globally abundant but historically underrepresented (Verpoorter et al., 2014) small lakes into large-scale projections of ice phenology. Using these data, I developed predictive models to project future ice conditions under multiple Shared Socioeconomic Pathway (SSP) scenarios (O'Neill et al., 2014). The results show that sustainable development pathways, as characterized by the SSP1 scenario, produce the most favorable outcomes for preserving and stabilizing lake ice. In contrast, warmer scenarios such as SSP3, characterized by global conflict, or SSP5, defined by continued reliance on fossil fuels, are projected to result in substantially greater and more variable losses in lake ice.

In Chapter 3 (Basu et al., in review), I expanded this analysis by examining projections in lake ice quality, focusing on the thickness and composition of black and white ice. This research represents the first large-scale projection of ice quality across the Northern Hemisphere. By

accounting for the structural differences between black and white ice, I assessed how climate-driven changes in ice composition influence the load-bearing capacity and the safety of winter activities. The results indicate that although overall ice thickness is projected to decline, the relative proportion of white ice within the ice column is expected to increase with a warming climate, consistent with previous findings (Weyhenmeyer et al., 2022). As with ice phenology, the SSP1 scenario yields the most favorable outcomes for maintaining and stabilizing lake ice quality. However, under warmer scenarios such as SSP3 and SSP5, losses of both black and white ice are substantially greater, exposing more than half of the Northern Hemisphere populations living near seasonally frozen lakes to increasingly hazardous ice conditions.

While Chapters 2 and 3 focused on large-scale patterns and projections, Chapter 4 examined the regional and local drivers that influence lake-ice dynamics. In this chapter, I investigated the relationships between lake ice phenology and surrounding land cover characteristics, including land cover types (developed, planted-cultivated, forested) as well as anthropogenic stressors, such as road density, population, and human footprint across five northern U.S. states. This work represents the first systematic assessment of how landscape context corresponds to differences in ice phenology among lakes within distinct regional environments. Additionally, by evaluating the relative importance of lake meteorological conditions, local land cover, and lake morphology, I identified how anthropogenic landscape characteristics influence ice dynamics and assessed the potential for regional and local management actions to help mitigate ice loss.

Future research could improve our understanding of lake ice dynamics by expanding on the spatial and ecological scope of current analyses. For example, including small lakes (less than 10 ha), extending coverage to lakes above 70°N, incorporating the Southern Hemisphere, and examining mountain lakes that freeze seasonally would provide a more comprehensive global assessment. In addition, many lakes will increasingly experience multiple freeze-thaw events annually due to climate warming (Sharma et al., 2021). Therefore, a more detailed investigation of these events is necessary, as they may serve as early indicators of lakes at risk of permanently losing ice cover. Further work is also needed to improve the representation of ice structure within ice-quality models. Lake ice is often simplified as a uniform column consisting of black ice overlain by white ice, yet more complex structures frequently develop within the ice

column, including multiple slush layers within white ice or air bubbles within black ice that alter mechanical strength and light transmission (Leppäranta, 2023). Incorporating these structural complexities into ice-quality predictive models would enhance the accuracy of future projections. Lastly, because anthropogenic pressures vary widely among regions, additional research is needed to understand how the landscape drivers of lake ice change differ geographically. Such insights will help guide context-specific management strategies aimed at preserving lake ice and the ecosystem services they support.

Ultimately, this research underscores the importance of lake ice as both a sensitive indicator of climate change and a critical component of freshwater ecosystems and northern communities. Through integrating large-scale climate projections with regional and local analysis, this thesis contributes a more comprehensive understanding of how lake ice is to evolve in a warming world and highlights the urgent need for coordinated global and local actions to preserve the ecological and societal benefits provided by seasonal lake ice.

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Appendices

Appendix A – Supplementary information for Chapter 2

1. Introduction

Section 1.1: This document shares figures and tables that are important for understanding the nature of the data used in the study and other supporting figures and information.

Section 1.2: This section contains a table providing a general overview of machine-learning tools used initially in this study to choose suitable algorithms and figures depicting such model performances.

Section 1.1: Supporting information for historical and future projections.

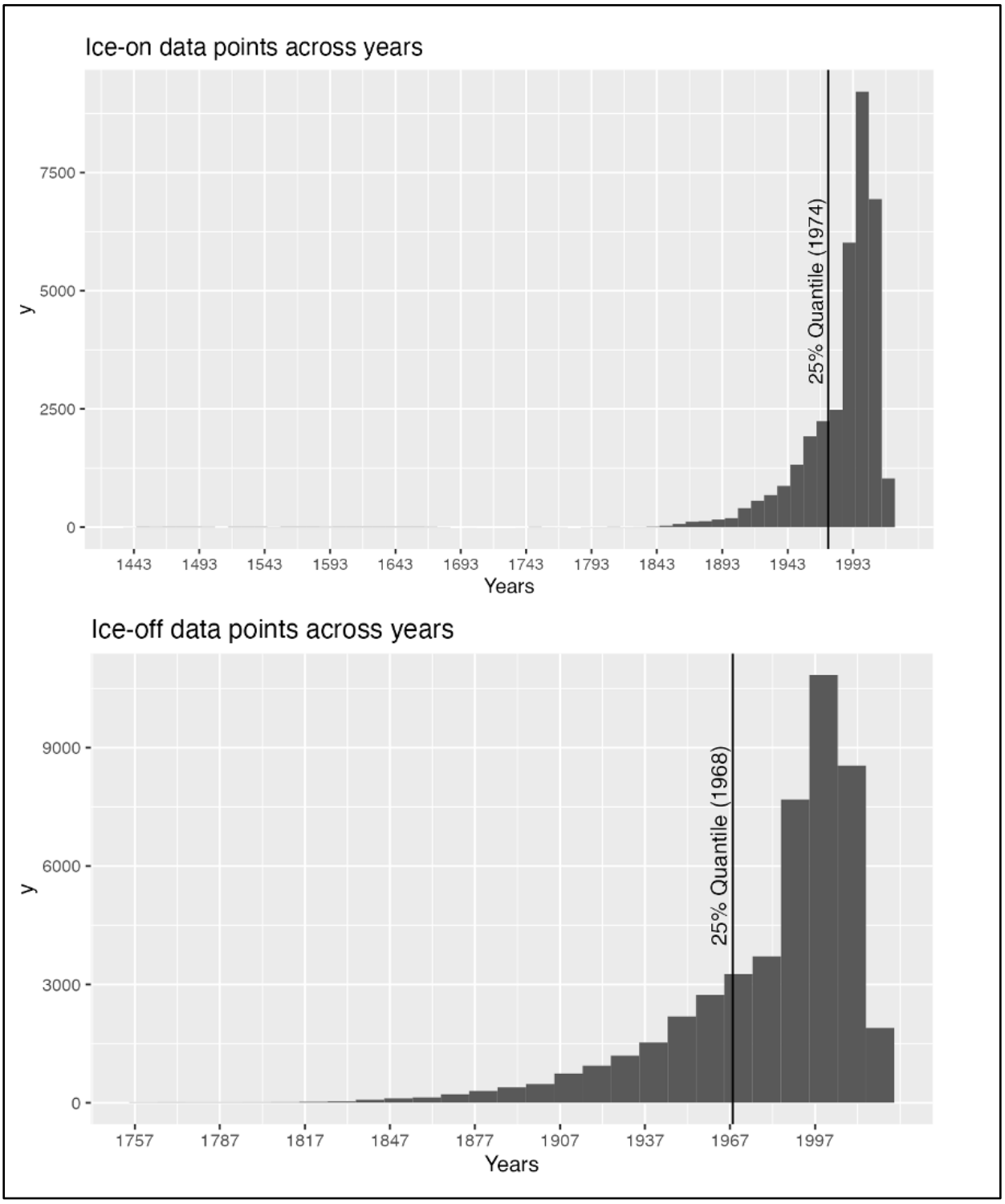


Figure S1: Distribution of ice records (ice-on and ice-off) over time. Ice-on (top) 25th quantile (year: 1974) and ice-off (bottom) 25th quantile (year: 1968).

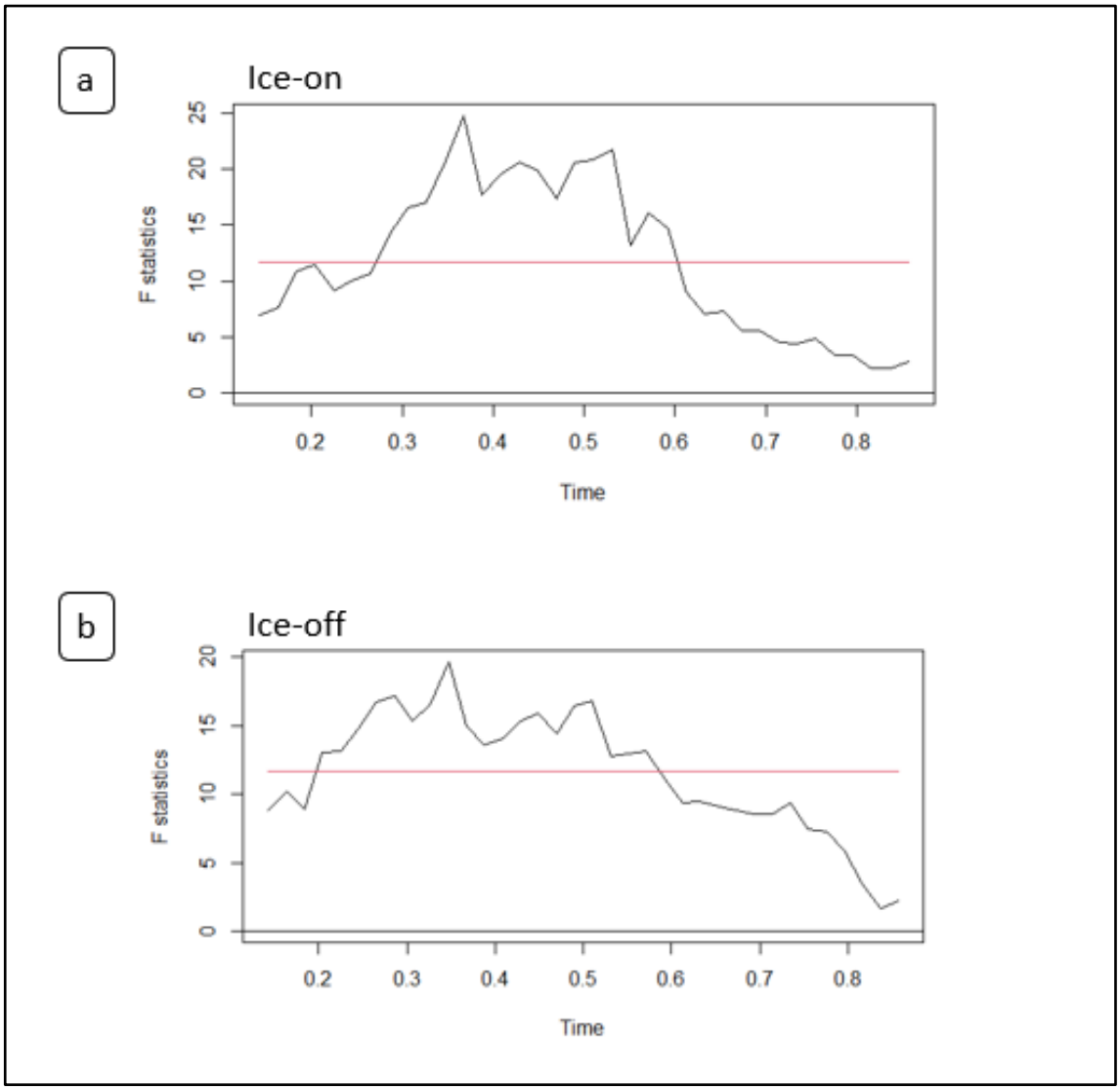


Figure S2: a) Ice on anomalies' 1st order autoregressive model breakpoint significance, and b) ice off anomalies' 1st order autoregressive model breakpoint significance. Here, the red line corresponds to an alpha value of 0.05.

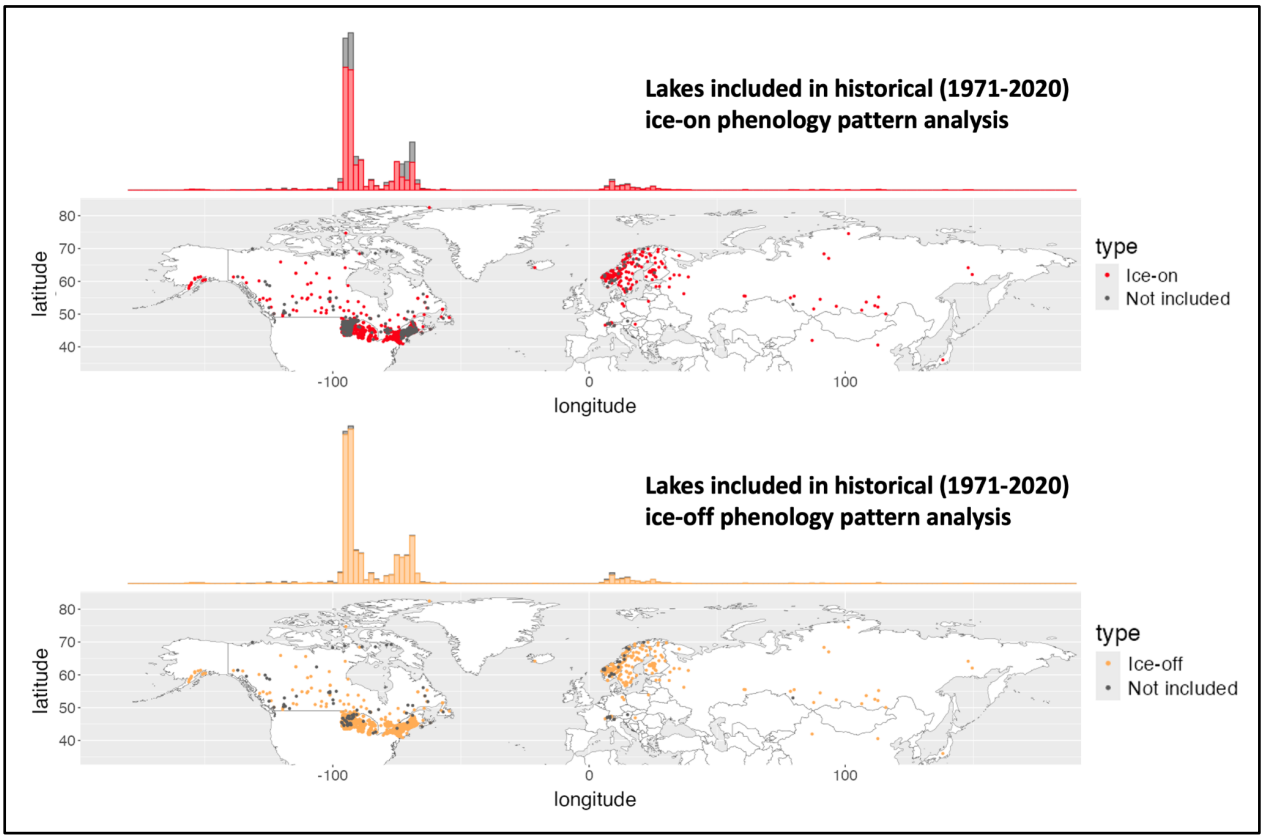


Figure S3: Distributions of lakes used for historical (1971-2020) ice-on (Top panel) and ice-off (bottom panel) dates.

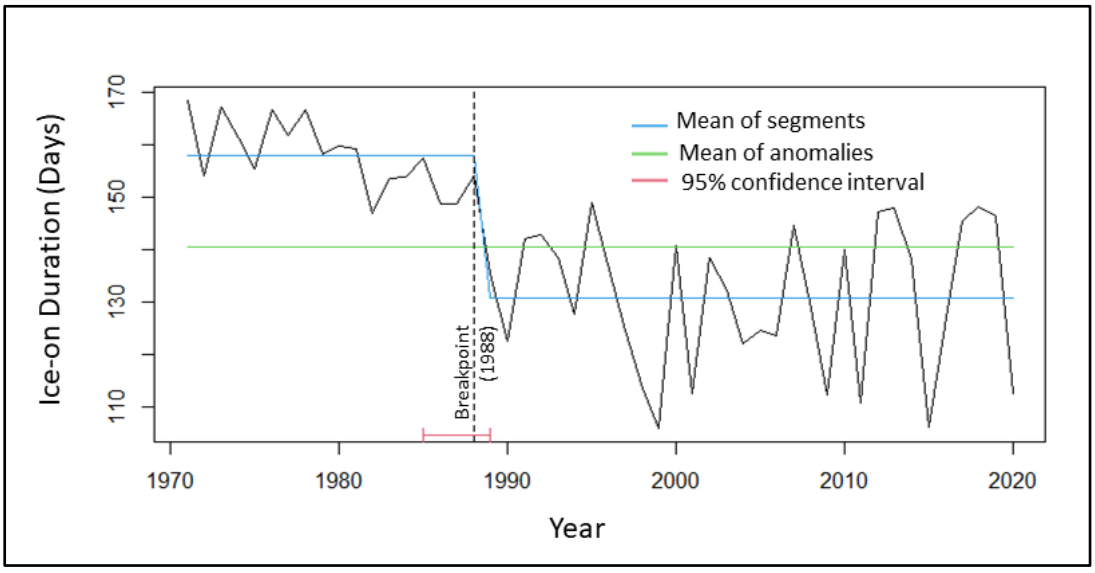


Figure S4: Breakpoint analysis of average duration spanning over the years 1971-2020.

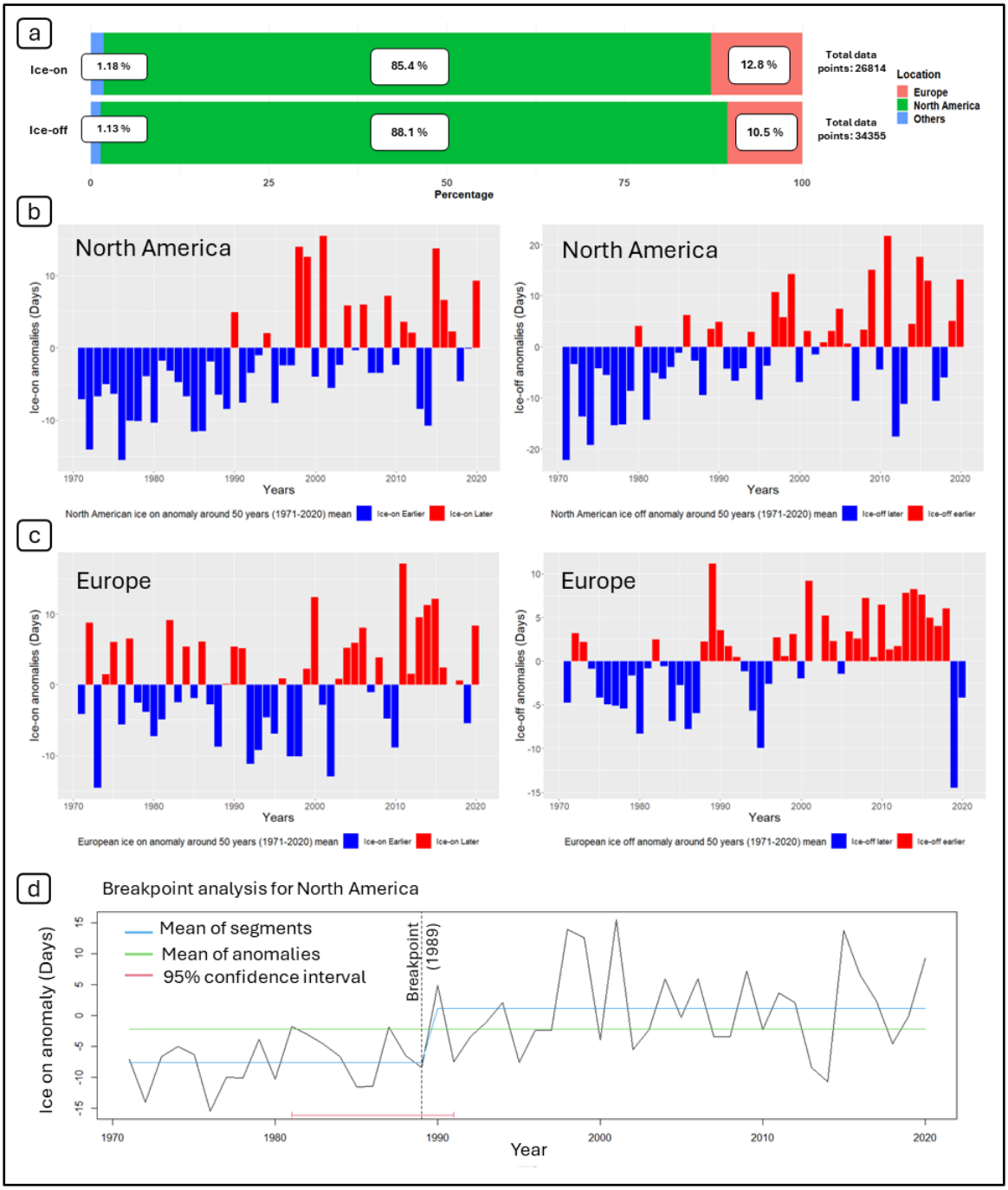


Figure S5: State of North American and European lake ice-on and ice-off for years 1971-2020: a) Percentage of data from North America, Europe, and other areas for ice-on and ice-off dates b)

Ice-on and ice-off anomalies in days for North America (Top row), c) Ice-on and ice-off anomalies in days for Europe (Bottom row), d) North American ice-on breakpoint.

Text box S1: North American (United States of America and Canada), and European (Norway, Switzerland, Finland, Sweden, Germany, Estonia, Iceland, Poland, Austria, and Hungary) ice-on anomalies indicate that the North American trend is likely dominating the global average pattern (Figure S5). Since most of the data points are from North America, followed by Europe and other countries (Japan, Russia, and China) (Figure S5a), regime shifts in the Northern Hemisphere have to be inferred with caution. Breakpoints were also identified for ice-on and ice-off anomalies in a similar way, as discussed in article section 2.2.1. We found that only the North American ice-on anomalies' breakpoint is significant (Figure S5d), which occurred in 1989. European ice-off anomalies indicate that there were multiple breakpoints but all of those breakpoints lack significance based on the criteria mentioned in section 2.2.1. This analysis hints that there was a probable difference in trends and breakpoints in different continents for ice-on and ice-off dates but owing to the scarcity of data, differences in continental scale historical ice-phenology patterns were inconclusive.

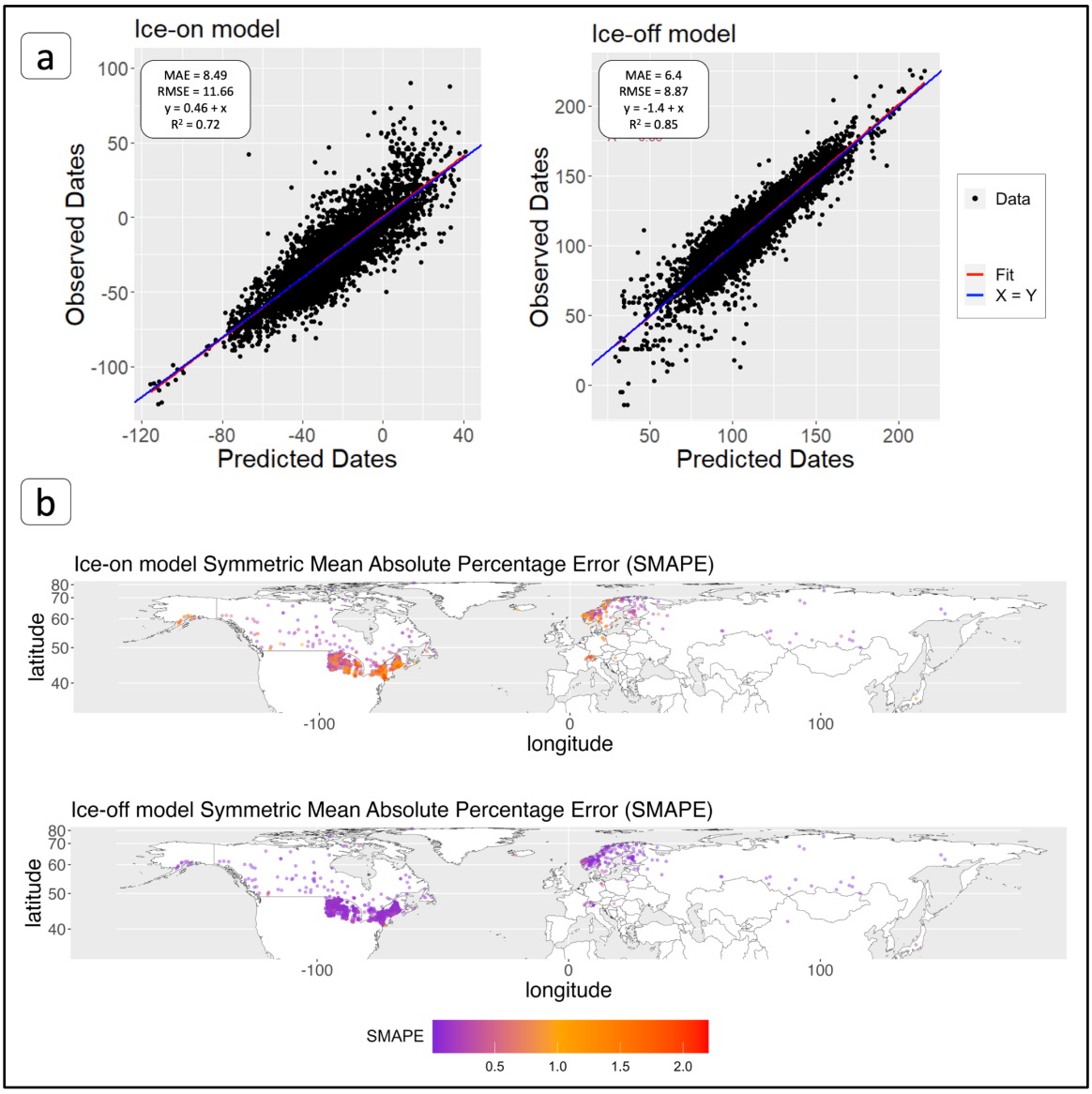


Figure S6: Ice-on and ice-off model predictive performances; a) Scatterplot of predicted and observed values for ice-on model (left) and ice-off model (right). b) Spatial distributions of ice-on (top) and ice-off (bottom) symmetric absolute mean percentage error (SMAPE) from respective testing datasets.

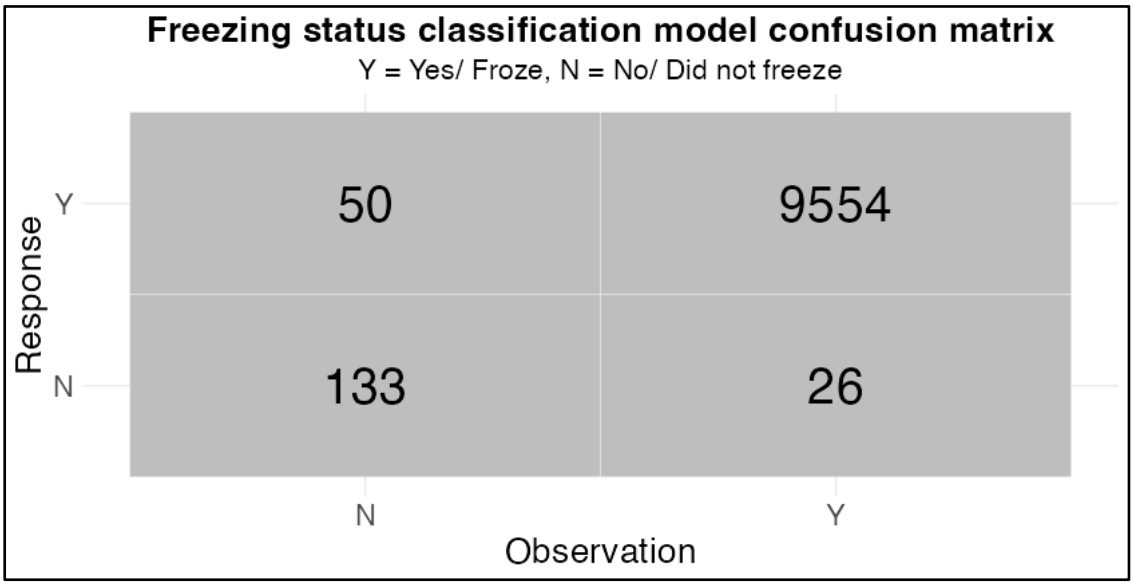


Figure S7: Confusion matrix for freeze/no-freeze classification model

Text box S2: The spatiotemporally cross-validated random forest ice-on model has "mtry" value of 2 and ice-off model has "mtry" of 3. Both models have a "ntree" value of 350. For the classification (freeze/no-freeze) model "mtry" value was 3 and "ntree" value was 475. Here, "mtry" is the number of randomly drawn variables from which each split is selected while growing a decision tree whereas ntree is the number of trees used to build the random forest model.

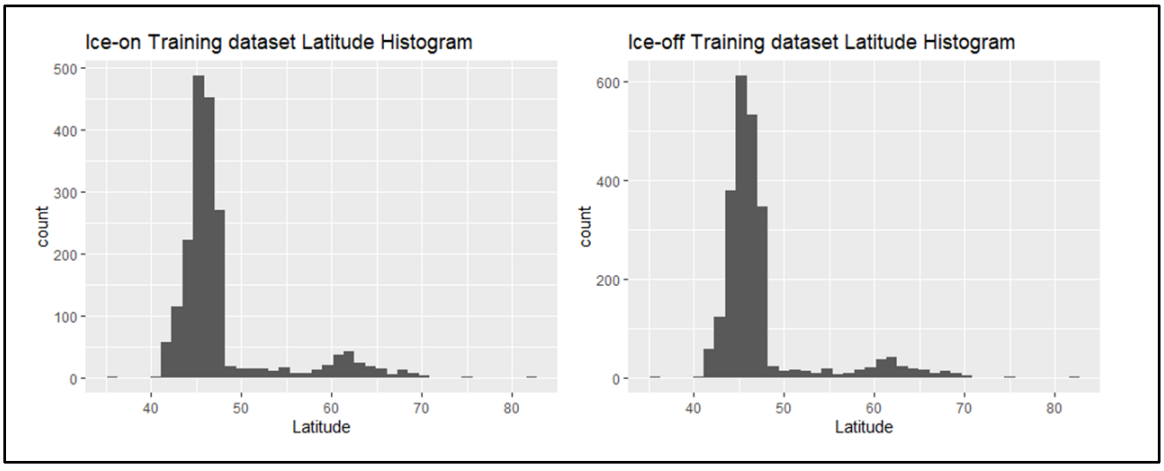


Figure S8: Distributions of lakes' latitude for training data for ice-on and ice-off models.

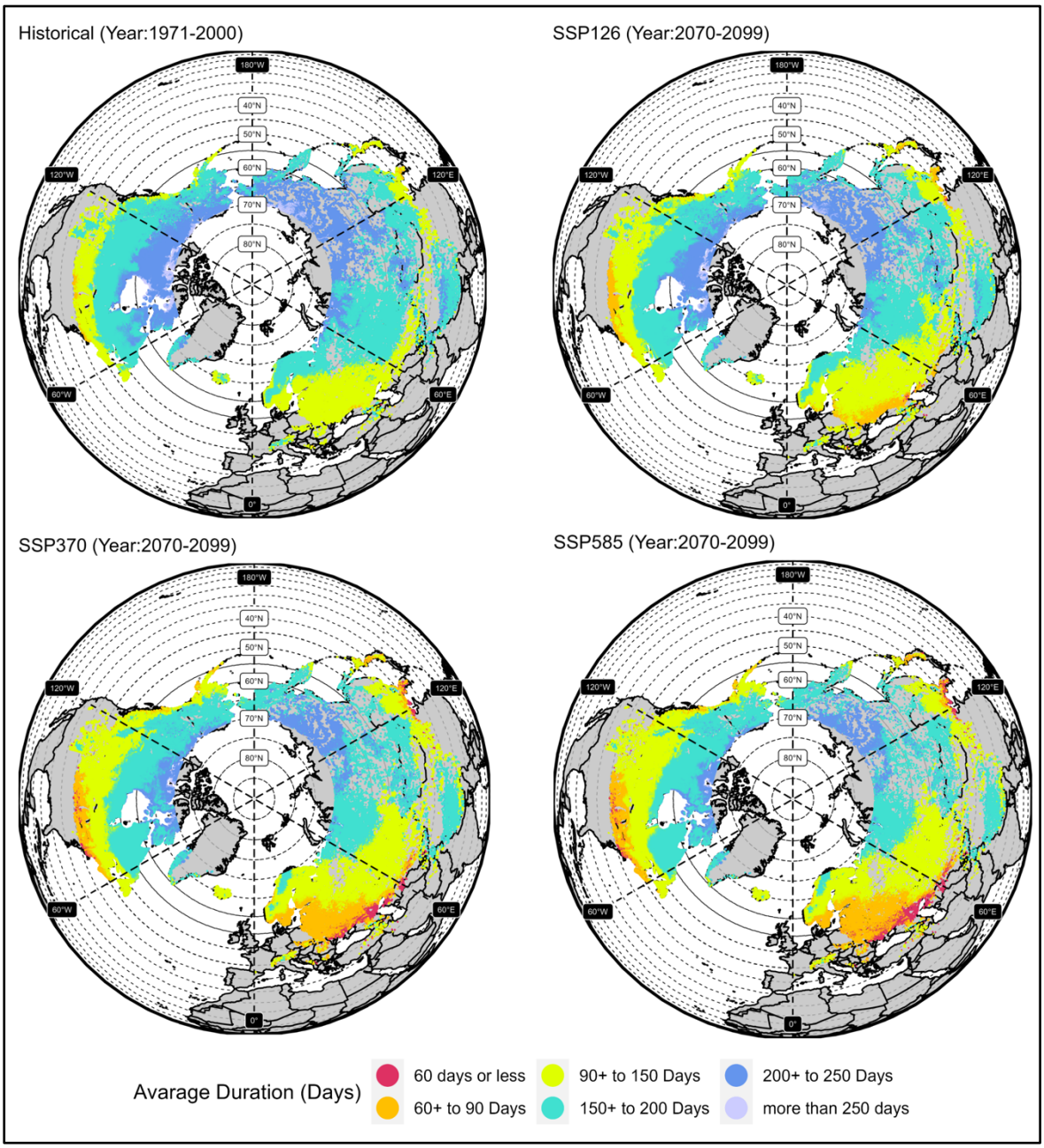


Figure S9: Projected spatial distributions in lake ice cover duration for future (2070-2099) SSP climate change scenarios.

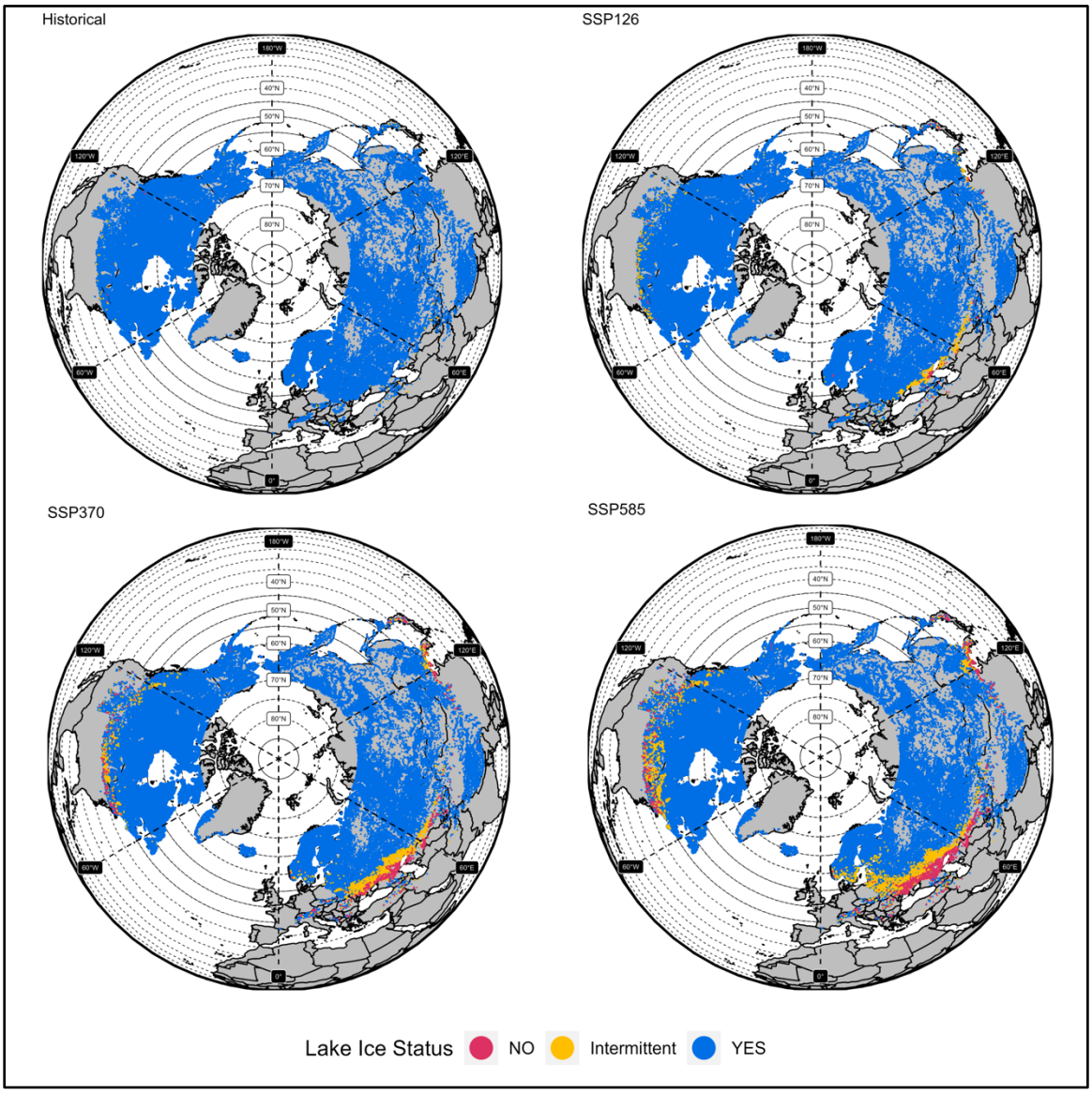


Figure S10: Spatial distribution of continuous freezing, intermittent freezing, and no freezing status of lake ice for historical (1971-2000) and future scenarios (SSP126, SSP370, and SSP585) calculated over the period 2070-2099.

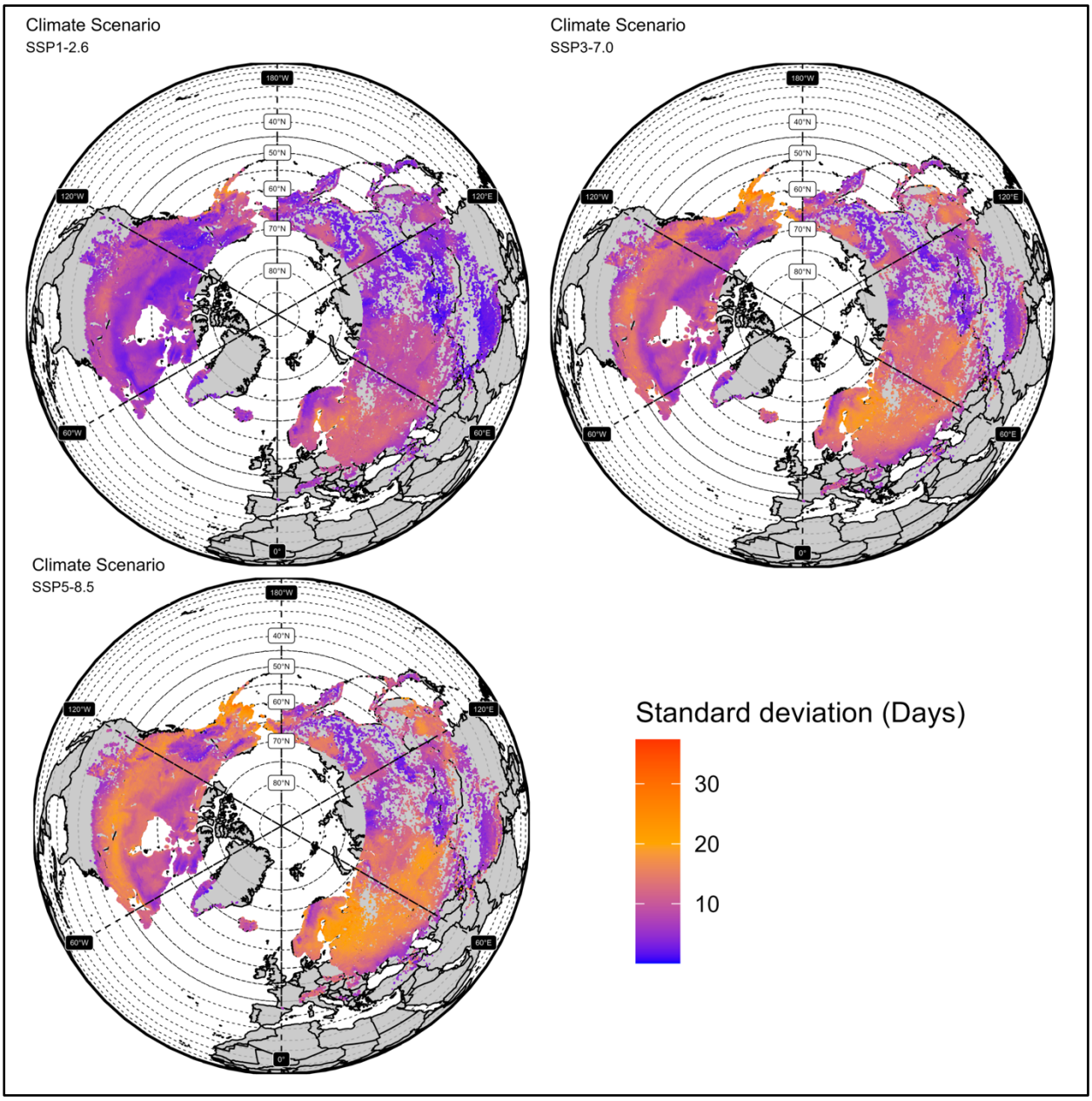


Figure S11. Standard deviations of ice duration for lakes across the Northern Hemisphere over the period 2015-2099 for a suite of climate change scenarios.

Table S1: Summary of the predictor variables for the lakes used in the random forest model.

			Min	**Percentiles**	**Max**

Variables	**Mean**	**SD**		**25**	**75**	
Lake Area (km^2)	167	1851	0.1	1	14	31968
Shoreline development	69	306	1.3	5.6	33	5332
Shoreline length (km)	2.4	1.9	1	1.5	2.7	35
Total Volume (million-m^3)	59329	1162944	0.13	4.3	128	23615000
Average Depth (m)	11	38	0.1	4	10	739
Elevation (m)	329	212	2	190	417	1795
Watershed Area (km^2)	4128	43165	0.1	14	348	919612
Maximum depth (m)	26	86	1.2	12	24	1642

Section 1.2: Initial Machine Learning Model Comparisons

For initially choosing the algorithm for ice phenology prediction, we tested several machine-learning models. We used popular machine learning that has different levels of complexity and is commonly used in ecology (Pichler and Hartig, 2023). We used multiple linear regression as our simplest model. We then conducted models of intermediate complexity, including lasso regression, ridge regression, elastic-net regression, and decision tree. Finally, we conducted models of higher complexity, which included support vector machine, k-nearest neighbors, random forest, and artificial neural network regression. Brief descriptions of the models used are summarized in Table S2. We tested each model's performance with our lake ice phenology data to choose the suitable machine learning algorithm for further analysis of data and future inferences (See section 2.2.2 in the manuscript)

The following R packages were used to conduct our analysis: multiple linear regression "stats" (R Core Team, 2021); lasso, ridge, and elastic-net regression "glmnet" (Friedman et al., 2010); support vector machine "kernlab" (Karatzoglou et al., 2004); k-nearest neighbours "mclust" (Scrucca et al., 2016); decision tree "rpart" (Therneau & Atkinson, 2022); and random forest "randomForest" (Liaw & Wiener, 2002). We used the "caret" (Kuhn, 2022) R package for cross-validation and model hyperparameter tuning.

We randomly split training and testing data into a 75:25 percent ratio. With the training dataset, we used 10-fold cross-validation for the lasso, ridge, and elastic-net regression and 10-fold repeated cross-validation with five repeats for all the other machine learning models. The predictor variables were centered (subtracting the mean of the predictor's data from the predictor values) and scaled (dividing the standard deviation from the predictor values) for training support vector machine, k-nearest neighbors, and ANN algorithms. To evaluate the final model, we compared RMSE (Root Mean Square Error), MAE (Mean Absolute Error), R-Square, and slope of the fitted line between predicted and actual values obtained from the testing dataset. Results are shown in Table S3. We found that Random Forest produced significantly better results than other tested algorithms and was chosen for further detailed analysis with spatiotemporal split and 10-fold spatiotemporal cross-validation (See section 2.2.2 in the manuscript).

The code for the models is given in the GitHub repository link: https://github.com/Aman-Basu/Northern-Hemisphere-Lake-Ice-Phenology-Project. The trained model files are provided in the Figshare repository link: https://figshare.com/account/articles/24208374.

Table S2: Descriptions of models used for training and testing ice-phenology models

Model	Model Description
Multiple linear regression	This type of model uses multiple (two or more) explanatory variables to model linear relationships with the response variable. (Jobson, 1991)
Ridge regression	This is a type of multiple linear regression that addresses the problem of multicollinearity and is more robust than multiple linear regression in tackling overfitting in the model. It adds a penalty term to the traditional linear regression objective function, which is based on the sum of squared coefficients multiplied by a regularization parameter (lambda or α). The regularization term encourages the model to shrink the coefficient values toward zero, effectively reducing their impact on the final predictions. By doing so, ridge regression provides more stable and reliable estimates of the coefficients, especially when dealing with datasets that have high multicollinearity. (Saleh et al., 2019)
Lasso regression	Lasso stands for "Least Absolute Shrinkage and Selection Operator," and this regression is another variant of multiple linear regression that addresses multicollinearity and performs variable selection simultaneously. Like ridge regression, it adds a penalty term to the linear regression objective function, but instead of the sum of squared coefficients, it uses the sum of the absolute values of the coefficients multiplied by a regularization parameter (lambda or α). These characteristics enable the lasso regression to be able to shrink some

	coefficients to exactly zero, effectively performing variable selection by eliminating certain independent variables from the model. By reducing the number of variables in the model, lasso regression can simplify the interpretation and improve the model's generalization ability. (Saleh et al., 2019)
Elastic-net regression	Elastic-Net regression is a model that combines the properties of both ridge and lasso regression. It aims to address the limitations of each approach and provide a more flexible regularization technique for linear regression problems. Similar to ridge and lasso regression, elastic net adds a penalty term to the linear regression objective function. The penalty term includes a combination of both the sum of squared coefficients (ridge penalty) and the sum of the absolute values of the coefficients (lasso penalty), multiplied by respective regularization parameters (lambda or α and lambda or β). The regularization parameters control the amount of regularization applied to the model. (Saleh et al., 2019; Zou & Hastie, 2005)
Decision tree regression	Decision tree is a machine learning algorithm with a flowchart-like structure where each internal node represents a feature or attribute, each branch represents a decision rule, and each leaf node represents an outcome or prediction. This algorithm builds the tree by recursively partitioning the data based on the values of different features. It selects the best feature at each node that maximizes the information gain or reduces the impurity of the data to have more homogeneous subsets of data within each branch. Decision trees are known for their interpretability and ease of understanding but are prone to overfitting,

	especially when they grow too deep or when the dataset has noise or outliers (Breiman, 2017; Loh, 2011).
Random forest regression	Random Forest is an ensemble machine learning method that combines multiple decision trees to create a more robust and accurate predictive model. Random Forest is robust against overfitting, handles high-dimensional datasets well, and can capture complex relationships between features and the target variable (Breiman, 2017; Cutler et al., 2012).
K- nearest neighbours regression	This machine learning algorithm determines the predicted value for a new data point by considering the average (or weighted average) of the target values of its k nearest neighbors. The "k" in KNN represents the number of neighboring data points considered. This regression method can be sensitive to the value of k, and the choice of distance metric is crucial (Kramer, 2013).
Support vector machine regression	The goal of this machine learning regression model is to find a function that best fits the data while maintaining a maximum margin. It aims to find a hyperplane that includes as many data points within a specified margin (epsilon) around the predicted values (Awad & Khanna, 2015).
Artificial neural network regression	Artificial neural networks are a class of machine learning algorithms inspired by the structure and functioning of biological neural networks in the human brain. In regression problems, the neural network is trained to predict a continuous target variable based on input features. The network consists of interconnected layers of artificial neurons, also known as nodes or units. The nodes in each layer receive weighted inputs from the previous layer and apply an activation function to produce an output (Aggarwal, 2018; Nielsen, 2015).

Table S3: Evaluation matrices of tested models. RMSE (Root Mean Square Error) in days, MAE (Mean Absolute Error) in days, R^2, and Slope are obtained from the fitted linear regression line between predicted and actual values of the testing dataset. Here, all the p values are statistically significant to a level of 0.05

Regression Model	**Evaluation matrices (Ice-on model)**					**Evaluation matrices (Ice-off model)**				
	RMSE	**MAE**	**R^2**	**Intercept**	**Slope**	**RMSE**	**MAE**	**R^2**	**Intercept**	**Slope**
Multiple linear	15.67	11.76	0.5	-0.34	1	14	9.93	0.64	-2.4	1
Ridge	16.3	12.08	0.48	2.1	1.1	14.21	10.12	0.63	-11	1.1
Lasso	15.67	11.77	0.5	-0.25	1	14	9.93	0.64	-2.5	1
Elastic-net	15.67	11.77	0.5	-0.23	1	14	9.93	0.64	-2.5	1
Decision tree	16.23	12.3	0.46	-0.07	1	13.56	9.97	0.66	-1.1	1
Random forest	11.61	8.61	0.72	-0.003	1	8.77	6.28	0.86	-1.1	1
Random forest (with spatio-temporal cv)*	11.66	8.49	0.72	0.46	1	8.87	6.4	0.85	-1.4	1

K-nearest neighbours	12.95	9.59	0.66	-0.8	0.97	9.8	6.94	0.82	-0.51	1
Support vector machine	13.35	9.96	0.64	1.3	1	10.26	7.3	0.81	-4.1	1
Artificial neural network	13.11	9.9	0.65	-0.67	0.99	10.11	7.33	0.81	0.38	0.99

*The model is used for future climate projections

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Appendix B – Supplementary information for Chapter 3

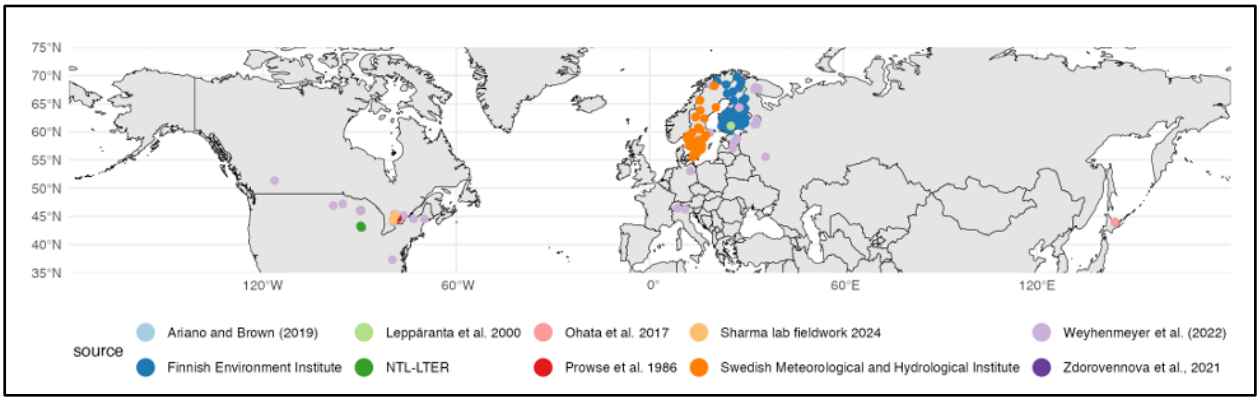
Supplementary Table 1: List of the datasets used for building ice quality models, ice quality projections, and assessing risk to human life.

Datasets	**Model building (Source)**	**Future Projections (Source)**
Ice quality	*In situ* data from 10 sources (Supplementary Table 2)	Not applicable
Meteorology	ERA5-Land (Muñoz Sabater, J., 2019)	ISIMIP3b (ISIMIP3b bias-adjusted atmospheric climate input data, 2021)
Lake morphology	HydroLAKES (Messager et al., 2016)	HydroLAKES (Messager et al., 2016)
Land use	HILDA+ (Winkler et al., 2021)	LUH2 (Hurtt et al., 2022)
Human population	Not applicable	Global 1 km Grid Population Projection 2020-2100 under SSPs (Wang et al., 2022)

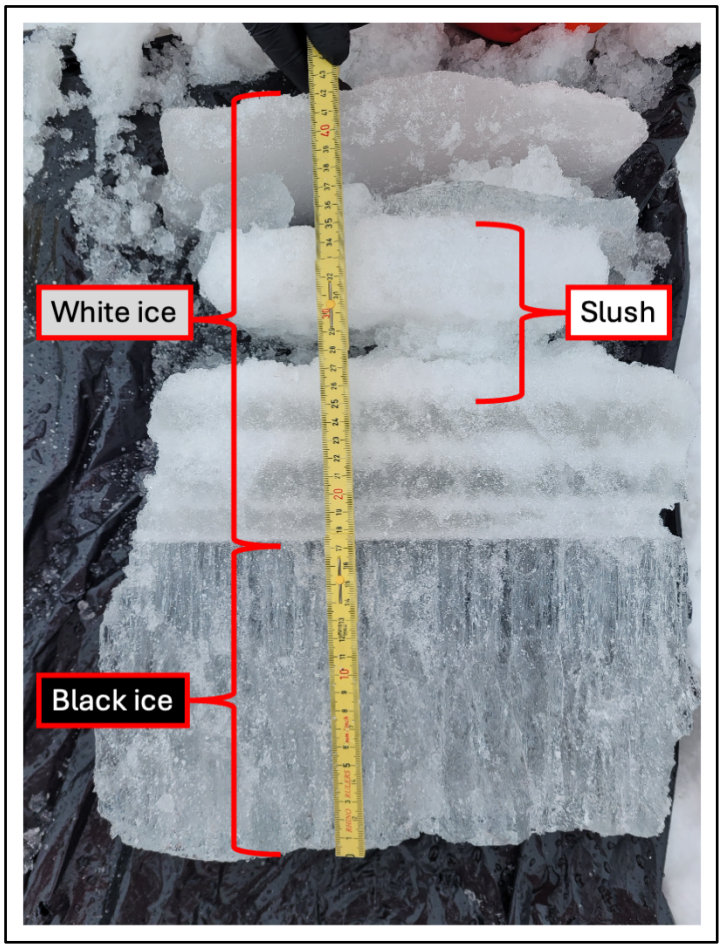
Supplementary Table 2: List of the ice quality data sources used for building the black and white ice models.

Ice quality data sources	**Data type**	**Number of lakes**	**Years measured**	**Ice thickness measurements**		
				Total	**Black ice**	**White ice**
Ariano and Brown (2019)	Secondary	2	2016 - 2017	70	70	69
Weyhenmayer et al. (2022)	Secondary	31	2020- 2021	92	92	92
Finnish Environmental Institute (2024)	Secondary	54	2014 - 2024	4848	4848	4848
Magnuson and Carpenter (2023): NTL-LTER	Secondary	11	1982-2023	903	903	903
Zdorovennova et al. (2021)	Secondary	1	1995 - 2020	39	39	39

Swedish Meteorological and Hydrological Institute (2024)	Secondary	36	1950 - 2019	17594	17563	17594
Leppäranta et al. (2000)	Secondary	1	1993-1999	7	7	7
Ohata et al. (2017)	Secondary	1	2013-2016	9	9	9
Prowse et al. (1986)	Secondary	1	1975 - 1976	13	13	13
Sharma lab fieldwork (2024)	Primary	2	2024	20	20	20



Supplementary Figure 1: Spatial distribution of ice quality data compiled for this study. The colored points represent the ten different data sources.

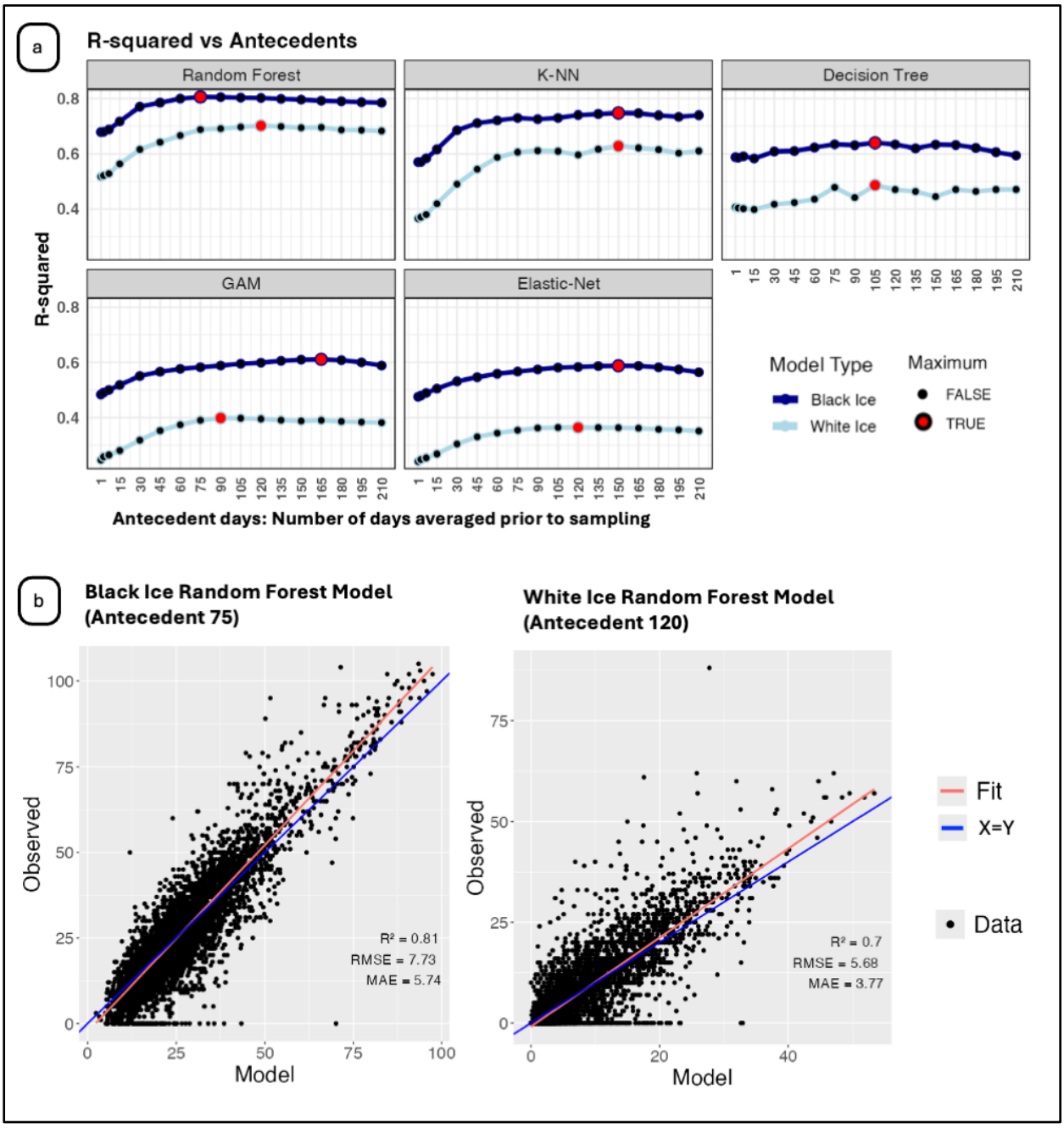


Supplementary image 1: Ice column depicting black ice at the bottom and white ice at the top with slush layers in between. The picture of the ice column was taken at Paint Lake, Ontario, Canada (45.217379, -78.945463) on March 25, 2025. Photo courtesy: Joshua Culpepper and Ryan Scott.

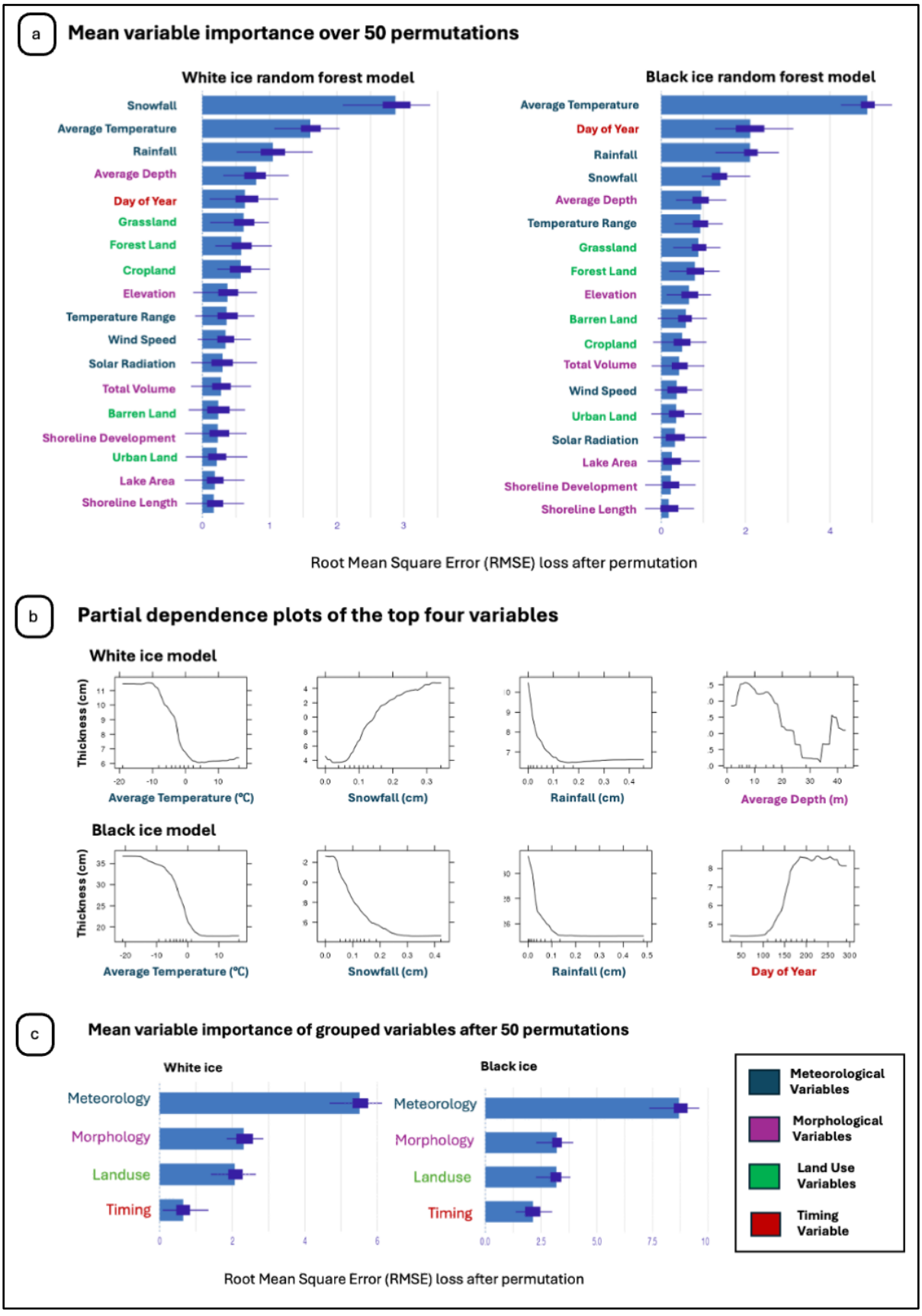
Supplementary Table 3: Categories combined to harmonize HILDA+ (used for training and testing the model) and LUH2 (used for model projection of historical and future ice quality).

Land use classification in HILDA+	**Land use classification in LUH2**	**Land use variables used in this study**
Forest	Forested primary land Potentially forested secondary land	Forest

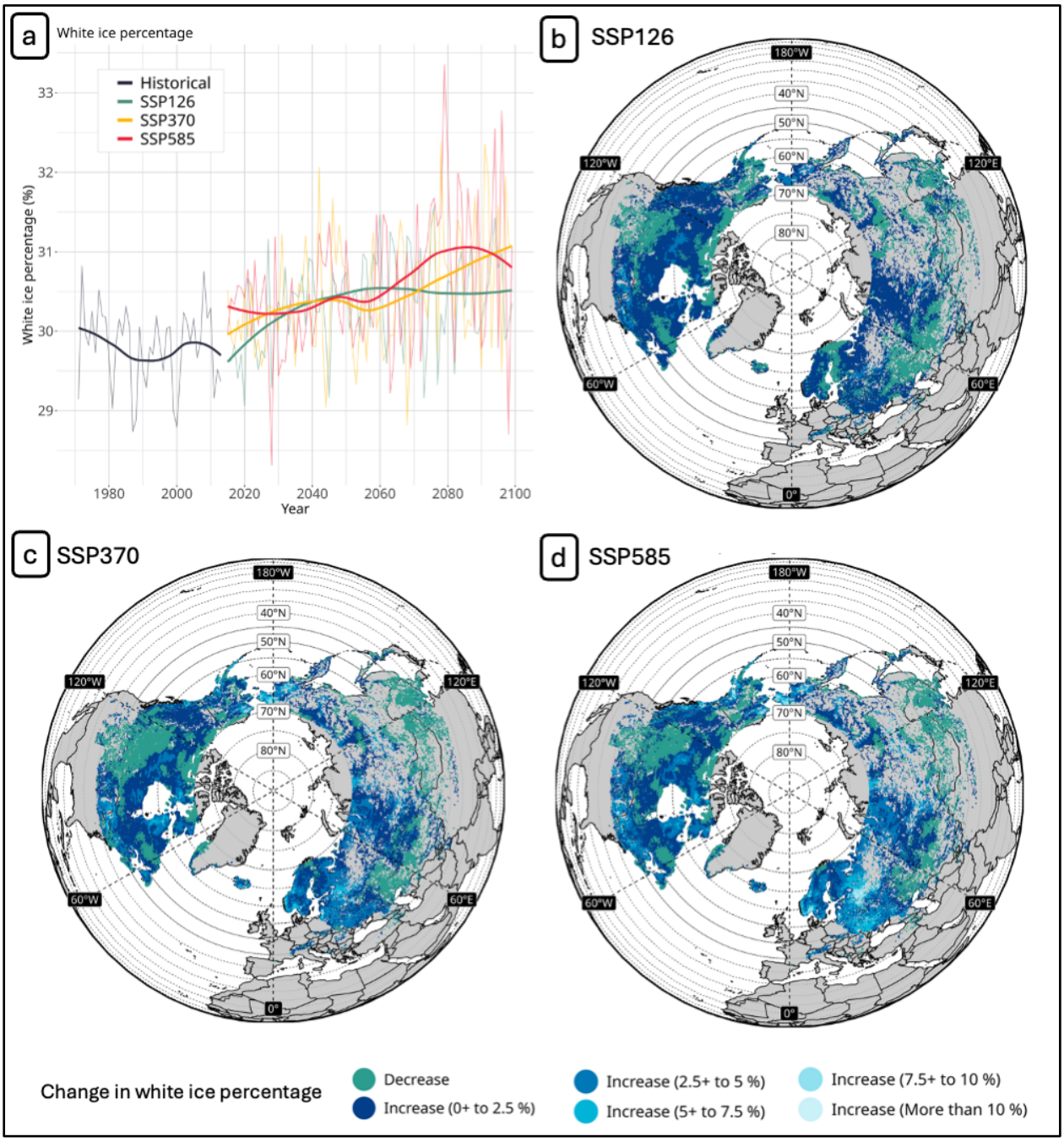
Pasture/Rangeland Unmanaged Grass/Shrubland	Managed pasture Rangeland	Grassland
Sparse/No vegetation	Non-forested primary land Potentially non-forested secondary land	Barren
Cropland	C3 annual crops C3 perennial crops C4 annual crops C4 perennial crops C3 nitrogen-fixing crops	Cropland
Urban	Urban land	Urban



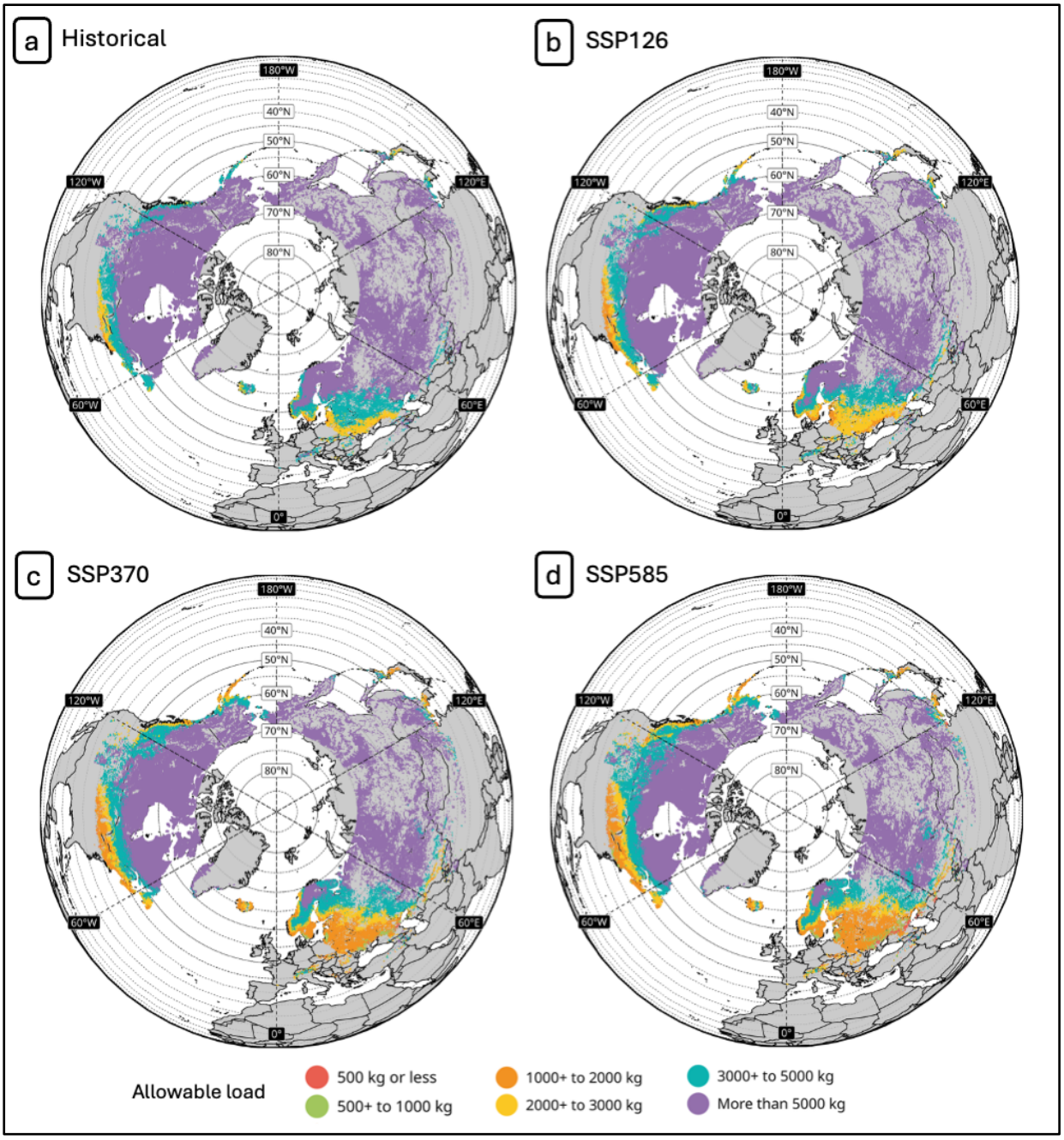
Supplementary Figure 2: a) R-squared for black and white ice models when considering meteorological conditions 1 - 210 days prior to sampling based on analyses using five machine learning models. b) Random forest model performance of black ice for the antecedent value of 75, and white ice for the antecedent value of 120 from the testing dataset.


a
Mean variable importance over 50 permutations
White ice random forest model
Snowfall
Average Temperature
Rainfall
Average Depth
Day of Year
Grassland
Forest Land
Cropland
Elevation
Temperature Range
Wind Speed
Solar Radiation
Total Volume
Barren Land
Shoreline Development
Urban Land
Lake Area
Shoreline Length
0
1
2
3
Black ice random forest model
Average Temperature
Day of Year
Rainfall
Snowfall
Average Depth
Temperature Range
Grassland
Forest Land
Elevation
Barren Land
Cropland
Total Volume
Wind Speed
Urban Land
Solar Radiation
Lake Area
Shoreline Development
Shoreline Length
0
2
4
Root Mean Square Error (RMSE) loss after permutation
b
Partial dependence plots of the top four variables
White ice model
Thickness (cm)
Average Temperature (°C)
Snowfall (cm)
Rainfall (cm)
Average Depth (m)
Black ice model
Thickness (cm)
Average Temperature (°C)
Snowfall (cm)
Rainfall (cm)
Day of Year
c
Mean variable importance of grouped variables after 50 permutations
White ice
Meteorology
Morphology
Landuse
Timing
0
2
4
6
Black ice
Meteorology
Morphology
Landuse
Timing
0.0
2.5
5.0
7.5
10
Meteorological Variables
Morphological Variables
Land Use Variables
Timing Variable
Root Mean Square Error (RMSE) loss after permutation

Supplementary Figure 3: a) Permutation importance of 18 predictors for white ice and black ice models. b) Partial dependence plots of the top five most important predictors. c) Grouped permutation importance of white ice and black ice models. All predictors are color-coded into four categories: meteorological variables (deep blue), lake morphological variables (Magenta), land use type variables (green), and timing variables (red).



Supplementary Figure 4: a) Changes in white ice percentage in total ice thickness. Here, the thinner line depicts the actual mean, while the thicker line depicts the local polynomial regression line from the locally estimated scatterplot smoothing (LOESS). Polar plots of white % changing for b) SSP126 scnarios, c) SSP370 scenario, and d) SSP585 scenario, respectively, over the future 30-year average (2070-2099) compared to the historical 30-year average (1971-2000).



Supplementary Figure 5: Polar plots of permissible loads for historical and future scenarios. Top left, Top right, bottom left, and right: Allowable loads for historical and three SSP126, SSP370, and SSP585 scenarios, respectively, over the future 30-year average (2070-2099). The seasonal average amount of allowable load is derived from Eq. (1).

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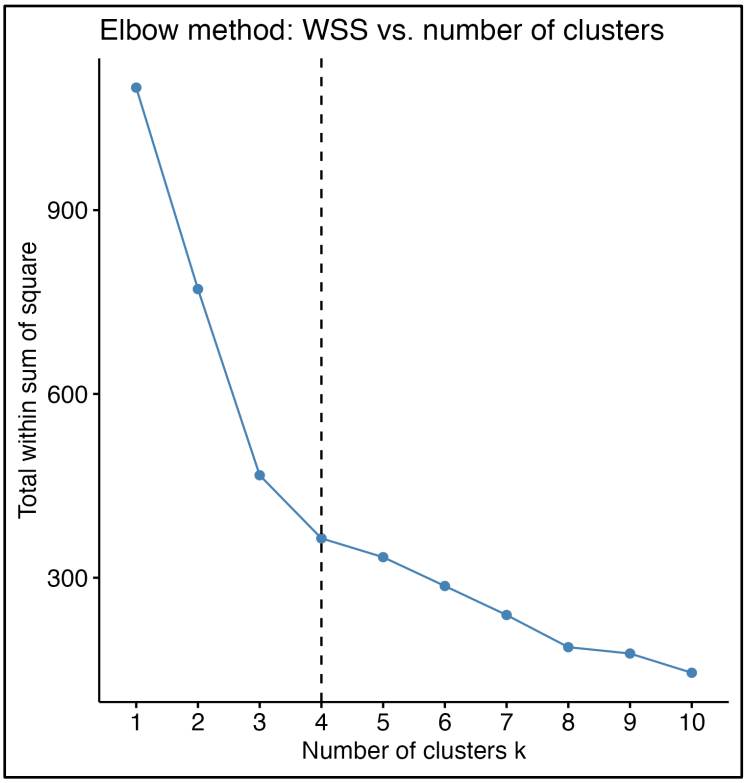
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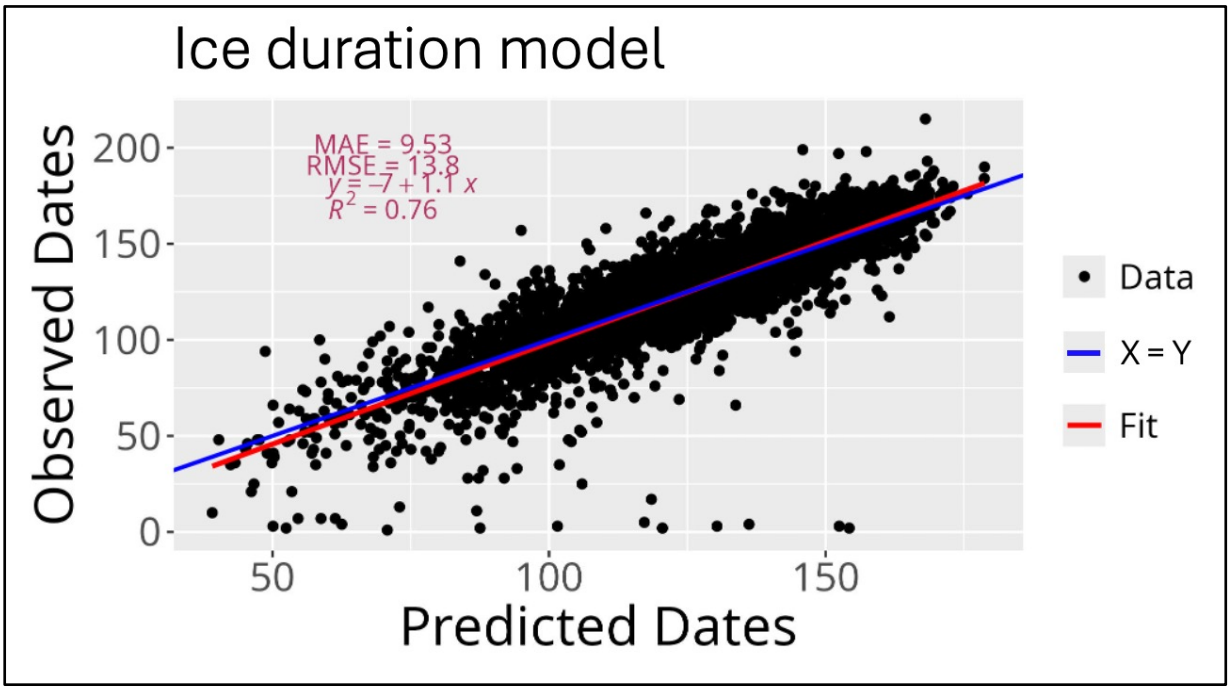
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Appendix C – Supplementary information for Chapter 4



Supplementary Figure 1: Elbow plot of the total within-cluster sum of squares (WSS) for k-means clustering up to 10 clusters (k = 1–10).



Supplementary Figure 2: Model performance for ice duration, showing observed versus predicted dates. Points represent individual observations; the blue line indicates the 1:1 perfect agreement line, and the red line shows the fitted regression between predictions and observations.

Appendix D – Chapter 2 copyright information

Parts of this thesis (Chapter 2) are reproduced from my published article (DOI: 10.1029/2023wr036392), which is distributed under the Creative Commons Attribution–NonCommercial–NoDerivatives (CC BY-NC-ND) license. This license permits reuse and redistribution with appropriate attribution for non-commercial purposes without modification. Since this thesis is a non-commercial academic work and the original article is properly cited, no further permission is required. More details are available at: https://creativecommons.org/share-your-work/cclicenses/.

Appendix E – Co-author permissions for inclusion of manuscripts in the Dissertation

Note: Chapters 1, 2, and 3 permission requested from co-authors are renumbered to 2, 3, and 4 in this thesis, with Chapter 1 serving as the general introduction.

Chapters 2,3 and 4: Sapna Sharma

Outlook

Re: Co-authorship permission

From Sapna Sharma <sapna.sharma23@gmail.com>
Date Tue 17/03/2026 13:04
To Aman Basu <amanbasu@yorku.ca>
Cc Sapna Sharma <sharma11@yorku.ca>

Hi Aman,

I approve all requests.
Thanks!
Sapna

On Tue, Mar 17, 2026 at 1:00 PM Aman Basu <amanbasu@yorku.ca> wrote:

> Dear Sapna,
>
> I hope you are doing well.
>
> I am writing to request your permission to include our co-authored work, “Phenological Shifts in Lake Ice Cover Across the Northern Hemisphere: A Glimpse Into the Past, Present, and the Future of Lake Ice Phenology,” in Chapter 1, “Unsafe Lake Ice Under Climate Change: Forecasting Lake Ice Quality for 1.12 Million Lakes Across the Northern Hemisphere,” in Chapter 2 and “Elucidating the extent of the influence of land cover on ice phenology across lakes in the northern contiguous United States: Implications for ecosystem management” in Chapter 3 of my dissertation/thesis, currently titled “The Future of Lake Ice: Drivers, Trends, and Projections of Ice Phenology and Ice Quality.”
>
> Because these chapters draw on material from our shared work, I would be grateful if you could provide written confirmation that you permit its inclusion in my dissertation/thesis. If required by the university, this permission may also be used as part of the submission record and for archiving or microfilming of the dissertation/thesis.
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> “I, [Full Name], give permission for the co-authored work entitled, ‘[Title of paper/manuscript/work]’ to be included in Chapter [X], ‘[Title of paper/manuscript/work]’ to be included in Chapter [X] and ‘[Title of paper/manuscript/work]’ in Chapter [X] of Aman Basu’s dissertation/thesis titled ‘[Dissertation/Thesis Title].’ I also give permission for this dissertation/thesis to be archived and microfilmed if required by the university.”
>
> Thank you very much for your time and support. Please let me know if you would like any additional details.
>
> Best regards,
> Aman Basu (He/Him)
> Ph.D. Candidate
> Department of Biology

Chapters 2 and 3: Joshua Culpepper

"I, Joshua Culpepper, give permission for the co-authored work entitled 'Phenological Shifts in Lake Ice Cover Across the Northern Hemisphere: A Glimpse Into the Past, Present, and the Future of Lake Ice Phenology' to be included in Chapter 1 and 'Unsafe Lake Ice Under Climate Change: Forecasting Lake Ice Quality for 1.12 Million Lakes Across the Northern Hemisphere' in Chapter 2 of Aman Basu's dissertation/thesis titled 'The Future of Lake Ice: Drivers, Trends, and Projections of Ice Phenology and Ice Quality.' I also give permission for this dissertation/thesis to be archived and microfilmed if required by the university."

Sincerely,

J. Culpepper

Joshua Culpepper, PhD
Dept. of Biology
York University

Chapter 2: Kevin Blagrave

Outlook

Re: Co-authorship permission

From Kevin Blagrave <kevin.blagrave@gmail.com>
Date Wed 18/03/2026 17:33
To Aman Basu <amanbasu@yorku.ca>
Cc Sapna Sharma <sapna.sharma23@gmail.com>

Hi Aman
I approve. And this is great news. Good luck!!

Kevin

> On Mar 17, 2026, at 1:00 PM, Aman Basu <amanbasu@yorku.ca> wrote:
>
> Dear Kevin,
>
> I hope you are doing well.
>
> I am writing to request your permission to include our co-authored work, “Phenological Shifts in Lake Ice Cover Across the Northern Hemisphere: A Glimpse Into the Past, Present, and the Future of Lake Ice Phenology,” in Chapter 1 of my dissertation/thesis, currently titled “The Future of Lake Ice: Drivers, Trends, and Projections of Ice Phenology and Ice Quality.”
>
> Because these chapters draw on material from our shared work, I would be grateful if you could provide written confirmation that you permit its inclusion in my dissertation/thesis. If required by the university, this permission may also be used as part of the submission record and for archiving or microfilming of the dissertation/thesis.
>
> For convenience, a simple statement or something similar, such as the following, would be sufficient:
>
> “I, [Full Name], give permission for the co-authored work entitled, ‘[Title of paper/manuscript/work]’ to be included in Chapter [X] of Aman Basu’s dissertation/thesis titled ‘[Dissertation/Thesis Title].’ I also give permission for this dissertation/thesis to be archived and microfilmed if required by the university.”
>
> Thank you very much for your time and support. Please let me know if you would like any additional details.
>
> Best regards,
> Aman Basu (He/Him)
> Ph.D. Candidate
> Department of Biology

Chapter 3: Iestyn Woolway

Outlook

Re: Co-authorship permission

From Iestyn Woolway (Staff) <iestyn.woolway@bangor.ac.uk>
Date Tue 17/03/2026 13:17
To Aman Basu <amanbasu@yorku.ca>

Dear Aman,

I hope you're doing well, and thank you for reaching out.

I'm very happy to provide permission for you to include our co-authored work, *"Unsafe Lake Ice Under Climate Change: Forecasting Lake Ice Quality for 1.12 Million Lakes Across the Northern Hemisphere,"* in Chapter 2 of your dissertation/thesis, *"The Future of Lake Ice: Drivers, Trends, and Projections of Ice Phenology and Ice Quality."*

For clarity and for your submission records, please feel free to use the following statement:

"I, Iestyn Woolway, give permission for the co-authored work entitled, 'Unsafe Lake Ice Under Climate Change: Forecasting Lake Ice Quality for 1.12 Million Lakes Across the Northern Hemisphere,' to be included in Chapter 2 of Aman Basu's dissertation/thesis titled 'The Future of Lake Ice: Drivers, Trends, and Projections of Ice Phenology and Ice Quality.' I also give permission for this dissertation/thesis to be archived and microfilmed if required by the university."

Please let me know if you need anything further or if any additional documentation would be helpful.

Best regards,
Iestyn

From: Aman Basu <amanbasu@yorku.ca>
Date: Tuesday, 17 March 2026 at 17:00
To: Iestyn Woolway (Staff) <iestyn.woolway@bangor.ac.uk>
Subject: Co-authorship permission

Dear Iestyn,

I hope you are doing well.

I am writing to request your permission to include our co-authored work, "Unsafe Lake Ice Under Climate Change: Forecasting Lake Ice Quality for 1.12 Million Lakes Across the Northern Hemisphere," in Chapter 2 of my dissertation/thesis, currently titled "The Future of Lake Ice: Drivers, Trends, and Projections of Ice Phenology and Ice Quality."

Because these chapters draw on material from our shared work, I would be grateful if you could provide written confirmation that you permit its inclusion in my dissertation/thesis. If required by

Chapters 3 and 4: Kevin Vikstrom

Permission to include co-authored work in dissertation/thesis

I, Kevin Vikstrom, hereby give permission for two of my co-authored works with the titles "Unsafe Lake Ice Under Climate Change: Forecasting Lake Ice Quality for 1.12 Million Lakes Across the Northern Hemisphere" and "Elucidating the extent of the influence of land cover on ice phenology across lakes in the northern contiguous United States: Implications for ecosystem management" to be included in Chapter 2 and 3 of Aman Basu's dissertation. The dissertation is currently titled "The Future of Lake Ice: Drivers, Trends, and Projections of Ice Phenology and Ice Quality". Furthermore, I also give permission for this dissertation/thesis to be archived and microfilmed if required by the university."

Kevin Vikstrom, 2026-03-18, Toronto, Canada



Chapters 3 and 4: Faith Ferrato

Outlook

Re: Co-authorship permission

From Faith Ferrato <faithfer@yorku.ca>
Date Tue 17/03/2026 13:53
To Aman Basu <amanbasu@yorku.ca>

“I, FAITH FERRATO, give permission for the co-authored work entitled Unsafe Lake Ice Under Climate Change: Forecasting Lake Ice Quality for 1.12 Million Lakes Across the Northern Hemisphere,” in Chapter 2 and “Elucidating the extent of the influence of land cover on ice phenology across lakes in the northern contiguous United States: Implications for ecosystem management” in Chapter 3 of Aman Basu’s dissertation/thesis titled ‘The Future of Lake Ice: Drivers, Trends, and Projections of Ice Phenology and Ice Quality.’ I also give permission for this dissertation/thesis to be archived and microfilmed if required by the university.”

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From: Aman Basu <amanbasu@yorku.ca>
Sent: Tuesday, March 17, 2026 1:00:00 PM
To: Faith Ferrato <faithfer@yorku.ca>
Subject: Co-authorship permission

Dear Faith,

I hope you are doing well.

I am writing to request your permission to include our co-authored work, “Unsafe Lake Ice Under Climate Change: Forecasting Lake Ice Quality for 1.12 Million Lakes Across the Northern Hemisphere,” in Chapter 2 and “Elucidating the extent of the influence of land cover on ice phenology across lakes in the northern contiguous United States: Implications for ecosystem management” in Chapter 3 of my dissertation/thesis, currently titled “The Future of Lake Ice: Drivers, Trends, and Projections of Ice Phenology and Ice Quality.”

Because these chapters draw on material from our shared work, I would be grateful if you could provide written confirmation that you permit its inclusion in my dissertation/thesis. If required by the university, this permission may also be used as part of the submission record and for archiving or microfilming of the dissertation/thesis.

For convenience, a simple statement or something similar, such as the following, would be sufficient:

“I, [Full Name], give permission for the co-authored work entitled ‘[Title of paper/manuscript/work]’ to be included in Chapter [X] and ‘[Title of paper/manuscript/work]’ in Chapter [X] of Aman Basu’s dissertation/thesis titled ‘[Dissertation/Thesis Title].’ I also give permission for this dissertation/thesis to be archived and microfilmed if required by the university.”

Thank you very much for your time and support. Please let me know if you would like any additional details.

Appendix F: Statement on contributions

Chapter 1: General introduction

Authors: Aman Basu, Faith R. Ferrato, Sapna Sharma

The general introduction was written by AB, edited by FF and SS.

Chapter 2: Phenological Shifts in Lake Ice Cover Across the Northern Hemisphere: A Glimpse Into the Past, Present, and the Future of Lake Ice Phenology.

Authors: Aman Basu†, Joshua A. Culpepper†, Kevin Blagrave, Sapna Sharma

AB and SS conceived the research ideas and designed the study. AB developed the methodology, conducted the investigation, performed validation and formal analyses, curated the data (with support from KB), and produced the visualizations. AB and SS contributed resources. SS provided supervision, managed project administration, and secured funding. AB prepared the initial draft, and JC made substantial contributions to manuscript refinement, interpretation of results, and subsequent writing. AB, SS, JC, and KB reviewed and edited the manuscript. All authors contributed to successive drafts and approved the final manuscript for publication.

† These authors are considered co-first authors

Chapter 3: Unsafe Lake Ice Under Climate Change: Forecasting Lake Ice Quality for 1.12 Million Lakes Across the Northern Hemisphere.

Authors: Aman Basu, Kevin Vikström, Joshua A. Culpepper, Faith R. Ferrato, R. Iestyn Woolway, Sapna Sharma

AB, KV, and SS conceived the research ideas and designed the study. AB developed the methodology, conducted the investigation, performed validation and formal analyses, curated the data, and produced the visualizations. AB and SS contributed resources. KV and SS provided supervision, SS managed project administration, and secured funding. AB and KV wrote the original draft, and AB, KV, SS, FF, JC, and IW participated in the review and editing. All authors contributed to successive drafts and approved the final manuscript for publication.

Chapter 4: Elucidating the extent of the influence of land cover on ice phenology across lakes in the northern contiguous United States: Implications for ecosystem management.

Authors: Aman Basu, Kevin Vikström, Faith R. Ferrato, Sapna Sharma

AB, KV, and SS conceived the research ideas and designed the study. AB developed the methodology, conducted the investigation, performed validation and formal analyses, curated the data, and produced the visualizations. AB and SS contributed resources. KV and SS provided supervision, SS managed project administration, and secured funding. AB and KV wrote the original draft, and AB, SS, and FF participated in the review and editing. All authors contributed to successive drafts and approved the final manuscript for publication.

Chapter 5: General Conclusion

Authors: Aman Basu, Faith R. Ferrato, Sapna Sharma

The general conclusion was written by AB, edited by FF and SS.

Sincerely,
Aman Basu

Approved by,
Sapna Sharma, PhD
Professor of Biology