https://doi.org/10.5194/tc-2022-31
Preprint. Discussion started: 9 February 2022

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Global evaluation of process-based models with in situ observations to detect long-term change in lake ice

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Abstract. Lake ice phenology has been used extensively to study the impacts of anthropogenic climate change, owing to the widespread occurrence of lake ice and the length of time series available for such studies. The proliferation of process-based lake models and gridded climate data have enabled the modeling of ice phenology across broad spatial scales, for example where lakes are not sampled. In this study, we used ice phenology outputs from an ensemble of lake-climate model projections to directly compare their performance with in situ data. Generally, we found that the lake models captured the range of variability of observational records (RMSE ice on =22.9 days [4.7, 95.4]; RMSE ice off = 17.4 days [6.1, 76.5]), and particularly the long-term trends in temperate regions. However, the models performed poorly in extremely warm years or when there were rapid short-term changes in ice phenology. The location of the lakes, such as latitude and longitude, as well as lake morphology, such as lake depth and surface area, significantly influenced model performance. For example, the models performed best in shallow small lakes and worst in deep larger lakes. Our analysis suggests that the lake models tested can reliably estimate long-term trends in lake ice cover, particularly when averaged across large spatial scales, but widespread in situ observations are critical to capture extreme events.

1 Introduction

Anthropogenic climate change is increasingly evident from many observations around the world (Hulme, 2016; Roe et al., 2017; Rogora et al., 2018). Measurements of surface air temperature have identified a rapid warming of all corners of the earth over the past century, and climate models project continued warming in the future (IPCC, 2021). In lakes, one of the most direct indicators of human-induced climate change is the seasonal timing or occurrence of lake ice (Grant et al., 2021). Indeed, lake ice is considered an essential climate variable (Woolway et al., 2020) that serves as an excellent indicator of long-term changes in the climate (Magnuson et al., 2000; Sharma et al., 2019). As well as being an important climate indicator, lake ice also provides essential ecosystem services that are vital to northern communities, both culturally and economically (Magnuson and Lathrop, 2014; Knoll et al., 2019). Ice fishing provides recreational opportunities for millions of anglers, drives economic activity to small communities, and food provisioning of protein in the winter months (Knoll et al., 2019). For example, an ice fishing tournament in Minnesota such as the Brainerd Jaycees Ice Fishing Extravaganza can bring in $1 million USD in revenue to a small town (Knoll et al., 2019) and the fish caught from ice fishing in Lake Peipsi (Estonia) accounts for a large portion of the annual fish harvest (Orru et al., 2014). Ice cover can also influence the surface albedo and thermal capacity of a lake during winter which, consequently, affects the surface fluxes exchanged with the atmosphere. In turn, the presence/absence of lake ice can influence local weather (Balsamo et al., 2012) and, in some regions, make the difference between light or heavy snowfall in their near-vicinity (Wright et al., 2013). The ecosystem services provided by lake ice will be threatened by climate change as ice dwindles because of the close relationship that

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exists between air temperatures and the formation or persistence of lake ice (Filazzola et al., 2020). Understanding lake ice responses to climatic variations is therefore critical for anticipating the repercussions of climate change on lakes and their associated ecosystems.

Lake ice has dramatically changed in recent decades, with later ice formation, earlier ice melts, and shorter seasonal durations of ice cover (Magnuson et al., 2000; Benson et al., 2012; Sharma et al., 2021). More specifically, in the last 25 years, the rate of lake ice loss is six times faster than in the past 100 years (Sharma et al., 2021) and some lakes are beginning to not freeze at all in some winters (Sharma et al., 2019). Many of the earlier studies have benefitted from using direct human observations of ice cover collected over decades to centuries for hundreds of lakes around the Northern Hemisphere. However, there are an estimated 50 million lakes around the world that freeze each winter, but do not have long-term observations. Thus, quantifying changes in lake ice worldwide requires a modeling approach. However, trying to make reliable predictions of how lake ice responds to climatic variations is challenging, as lake ice is influenced by complex thermodynamic fluxes occurring at the lake surface and within the water column. In recent decades, process-based models that encapsulate the dominant physical processes occurring in lakes have been developed and subsequently used to quantify, among other things, long-term changes in ice cover across the Northern Hemisphere (Woolway and Merchant, 2019; Grant et al., 2021). However, no study to our knowledge has yet evaluated whether these global scale models can adequately capture the observed historic variability across temporal and spatial scales, nor evaluated the variability among the model projections i.e., to investigate if all lake models behave the same.

In this study, we aim to fill this knowledge gap by comparing global simulations of lake ice phenology from an ensemble of process-based lake models with direct observations of lake ice from Northern Hemisphere lakes. We compared the accuracy of predicting ice on and ice off of four lake models relative to in situ observational ice records during the historic period, from 1901 to 2020. The accuracy of models was assessed using the mean difference of ice on and ice off dates from modeled and in situ data, root mean squared error (RMSE), and differences in trends. We ask the following questions: (i) how well do lake models capture the timing and duration of observed seasonal ice cover? (ii) does model accuracy differ across lake types and climatic regions?, and (iii) do lake ice models better capture long-term observed variability compared to short-term change.

2 Materials and Methods

2.1 Data Acquisition

2.1.1 Lake ice simulations

Lake ice projections used in this study were simulated using an ensemble of process-based lake models, which contributed to the Inter-Sectoral Impact Model Intercomparison Project phase 2b (ISIMIP2b) Lake Sector (Vanderkelen et al., 2020; Woolway et al., 2021; Grant et al., 2021). These models include the Community Land Model version 4.5 (CLM4.5) (Lawrence et al., 2011), the Arctic Lake Biogeochemistry Model (ALBM) (Tan et al., 2018), SIMSTRAT-UoG (Goudsmit et al., 2002), and LAKE (Stepanenko et al., 2016). Each lake model was driven by climate data from four Earth System Models which contributed to phase 5 of the Coupled Model Intercomparison Project (CMIP5), GFDL-ESM2M, HadGEM2-ES, IPSL-CM5A-LR and MIROC5, after bias-adjustment to the EWEMBI reference dataset (Lange, 2016; Frieler et al., 2017). Historical simulations (1901-2005) represent a historical climate, whereas future projections (2006-2099) consider three Representative Concentration Pathways representing low greenhouse gas emissions (RCP 2.6), moderate emissions (RCP 6.0), and high emissions (RCP 8.5) (Van Vuuren et al., 2011). Following the ISIMIP2b global lake sector protocol, each of

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these lake-climate models were used to simulate daily lake ice cover at a 0.5°-by-0.5° grid resolution, based on the mean depth and surface area of all known lakes within a 0.5° grid (i.e., the average depth of all known lakes and the surface area covered). Notably, for each 0.5° grid worldwide, the lake models simulated the ice cover of a "representative lake", with its size and depth determined by the distribution of all known lakes within that grid. The locations, depths, and grid-scale fractions of lakes within each 0.5° grid were determined by the Global Lake Data Base version 1 (Kourzeneva, 2010; Subin et al., 2012; Choulga et al., 2014). Lake information was aggregated from the original 30 arc-second resolution to a 0.5°-by-0.5° grid lake depth field. Each of the lake models, except CLM 4.5 used the same lake depth information. In CLM4.5, every grid cell has a constant lake depth of 50 m. Post-processing of modeled lake ice cover was performed to attain homogenized ice onset, break-up and duration values following Grant et al., (2021). Furthermore, we converted the ice off and ice on dates to be centered around January 1st as 0. Hence, dates before January 1st are negative and dates after January 1st are positive.

2.1.2 In situ observations

We obtained 61,690 records of in situ observations for 2,658 lakes spanning from 1874 to 2020 (updated from Benson et al. 2000) that matched the gridded latitudes and longitudes from ISIMIP2b. For each 0.5° ISIMIP grid, we averaged the in situ observational data (i.e., ice on and ice off day of year) for the lakes in that grid, to obtain an in situ gridded average ice phenology. We then used the averaged in situ gridded data to compare the projections from the models for the same grids.

2.2 Data Analysis

First, we calculated the anomaly in ice on or ice off dates to identify the general trend in the models over the time-series. We calculated the average ice on or ice off date in the time series from the year 1901 to 1930. This is the baseline for the anomaly. For each year, we then subtracted the model's ice on or ice off value from this baseline, which provided the difference in ice on or ice off date over time.

2.2.1 Model Performance

We used three metrics to investigate the difference between the in situ observations and the process-based lake models, using modeled ice phenology for the period 1900-2020 including the historical observations from 1900-2005 and RCP 6.0 from 2006-2020 (Frieler et al., 2017; Vanderkelen et al., 2020). For both ice on and ice off we calculated: i. The Root Mean Squared Error (RMSE), ii. The difference in mean for the time series between the in situ observation and modeled data, and iii. The difference in trends between the in situ observations and modeled data. Each method was calculated for each grid cell where we had in situ observations. We describe each method in detail below. For each analysis, we performed a Kruskal-Wallis one-way analysis of variance to quantify if there were differences between the models, followed by a Tukey post-hoc analysis to identify which groups were different from each other. For each grid, we calculated the RMSE between the modeled data and the in situ observations. Briefly, we used the ISIMIP projections as the predicted data and the in situ observations as the actual data. Higher RMSE values indicated that the modeled ice on and ice off deviated more from the observation. For each grid, we averaged the values obtained by the model, calculating 'y' and averaged the values of the in situ observations, calculating 'x' over the whole time series. We then subtracted y from x. A positive value indicates that the model predicted later mean ice off or mean ice on dates. For each grid, we ran an Ordinary Least Squares (OLS) regression to obtain the trend (slope) that would indicate the change in ice on or ice off dates per year. We ran the OLS for both the modeled data and for the in situ observations, after which we subtracted the trends obtained from each other. A negative value suggests that the model predicted a slower change in ice on or ice off dates relative to the observations.

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2.2.2 Factors affecting model performance

We used random forest models to investigate the factors affecting RMSE and the mean difference between the models and the in situ observations. Our response variables were RMSE and mean difference in dates. Our explanatory variables were latitude, longitude, length of the time series in the grid, average depth of lakes in the grid, average area of the lakes in the grid, and the percentage of extreme events in the grid. An extreme event was defined as a day (for ice on or ice off) where the day was greater than 2 standard deviations from the mean of the distribution of ice on or ice off day of the year for the grid. We then counted how many of these extreme events occurred for each grid and divided them by the length of the time series, to obtain a percentage of extreme events. We used 100 trees for the random forests, with no depth limit on the trees (Breiman, 2001).

2.2.3 Length of time series

As the length of the time-series may affect how well the models performed relative to the in situ observations in terms of RMSE, mean difference, and trend difference, we divided the time series into 6 categories, with the categories being time-series length from 0-10 years, 11-20 years, 21-40 years, 41-80 years, and over 80 years. We subsequently performed a Kruskal-Wallis one-way analysis of variance to quantify if there were differences between the categories of time-series, followed by a Tukey post-hoc analysis to identify whether there were statistically significant differences in model performance with varying lengths of time-series.

2.3 Case Study - Extreme Events

To investigate how well the in situ observations fit within the range of the model outputs within a grid cell, we selected a grid where there were at least 3 lakes with in situ observations. We plotted the time-series of the in situ observations along with the range of all the model outputs. We then visually detected how well the models captured the in situ observations. We chose the grid cell containing Lakes Mendota, Monona, and Wingra because they have an extensive time series, experienced extreme events in recent years, and have varying lake areas and depths (Magee and Wu, 2017; Sharma et al., 2021).

3 Results

To explore how well the lake models matched real-world observations, we calculated the anomaly in ice on days and ice off days across all the models (Figure 1). Prior to 2005, the ice on anomaly varied between a minimum of -2 days and a maximum of 4 days. There is a general upward trend, indicating generally later ice on dates over time. Following the inclusion of RCP 6.0 after 2005, the models have increasingly larger anomalies, with the variation now ranging between -1 and 8 days. For ice off, the anomaly varies between -6 days and 4 days up to 2005, with a general declining trend, signifying earlier ice off over time. Following the inclusion of the RCP scenario, the ice off anomaly varies between -22 and 2 days, suggesting even earlier ice off dates in recent years.

3.1 Model Performance

There are differences among the lake models, when compared to in situ observations (Figure 2). For RMSE, there were significant differences across all of the four lake models (ALBM, CLM4.5, LAKE, and SIMSTRAT) for ice off ($p < 0.05$) and ice on ($p < 0.05$). For ice off, ALBM was not significantly different from CLM4.5 ($p > 0.05$) and SIMSTRAT ($p > 0.05$), but all other pairwise model comparisons were significantly different ($p < 0.05$). The greatest differences in ice off were between LAKE (mean=26.4 [11.6, 58.8] 95 % confidence interval) and ALBM (RMSE: mean=19.8 [9.3, 44.2]). For ice on, ALBM and CLM4.5 were not significantly different from each other ($p > 0.05$), and all other pairwise model comparisons were significantly different from each other ($p > 0.05$). Similar to ice off, the greatest differences in ice on were between LAKE (mean=20.7 [11.2, 37.8]) and ALBM (mean=16.6 [9.2, 34.5]). Using the mean difference metric, we found significant differences across all the four lake models for both ice off ($p < 0.05$) and ice on ($p < 0.05$). For ice off, all

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pairwise model comparisons were significantly different from each other ($p < 0.05$), with the greatest difference being between LAKE(mean=-17.7 [-55.5, 6.5]) and ALBM (mean=-2.2 [-38.2, 18.4]). For ice on, except between LAKE and the CLM4.5, all pairwise model comparisons were significantly different from each other ($p < 0.05$). The greatest difference was between LAKE (mean=-11.4 [-30.2, 9.7]) and ALBM (mean=9.2 [-2.2, 26.1]). We found no significant differences across the four models for ice on ($p > 0.05$) and ice on off ($p > 0.05$) when looking at the difference in trends.

3.2 Factors affecting model performance

We used random forests, based on 100 trees, to investigate the factors affecting RMSE and mean difference of the models. For RMSE, the model for ice on explained 84.9% of the variation and the model for ice off explained 66.4 % of the variation. For mean difference, the random forest explained 69.4 % of the variation for ice on and 43.2% of the variation for ice off.

For both ice on and ice off, the longitude of the lakes was the most important factor influencing RMSE (Figure 3). For ice on, the remaining important factors in order were average depth of the lakes in the grid, length of the time-series of the lakes, average area of the lakes in the grid, latitude of the lakes, and number of extreme events from the lakes in that grid. For ice off however, latitude was second most important, followed by area, length of the time-series, number of extreme events, and depth of the lakes. We observed some interesting relationships when examining the partial dependence plots (Figure 3) For ice on, the model depends less on the latitude of the lake in more northerly regions, however the opposite is observed for ice off. Interestingly, latitude has less of an effect on the RMSE in lakes found in mid-western USA. For ice on, RMSE depends more on the length of the time series the longer the time series. However, ice off is less dependent on the time series. For depth, area, number of extreme events, and longitude, similar patterns are generally observed in both ice on and ice off. Overall, we noticed that shallow small lakes had lower RMSE than deep large lakes.

3.3 Length of time series

We examined how the length of the time series influenced RMSE, mean difference and trend difference. For RMSE and mean difference, the difference among the models and among the binned year categories were significantly different ($p < 0.05$) for ice on and ice off (Figure 4). For ice on and RMSE, SIMSTRAT and ALBM were not significantly different from each other ($p > 0.05$) and there were no significant differences between grouped years of 0-10 and the other length categories (years 11-20, 21-40, 41-80, and > 80). For RMSE of ice off, CLM4.5 and ALBM were not significantly different from each other ($p > 0.05$), as well as SIMSTRAT and ALBM ($p > 0.05$). For the grouped years, there were no significant differences between the groups when the length of the time series was over 40 years ($p > 0.05$), and no significant difference between 0-10 and 21-40 years ($p > 0.05$).

For mean difference and ice on, all pairwise comparisons were significantly different from each other (< 0.05). When including binned years, pairwise differences between 0-10 and the other grouped years were not significant ($p > 0.05$), as well as between 21-40 and over 80 years ($p > 0.05$). For ice off, except for LAKE and CLM4.5, all models were significantly different from each other ($p < 0.05$). For the grouped years, there were no significant differences between pairs of categories of time-series length for 11-20 years and over 80, 0-10 and 21-40, 0-10 and 41-80, and 21-40 and 41-80 years ($p > 0.05$). For differences in trends, there were no significant differences among the models for either ice on or ice off ($p > 0.05$), indicating the models capture trends of the time-series similarly. However, there were differences among the grouped years. For ice on, except for between 21-40 and over 80 years, 41-80 and over 80 years, and 11-20 and 41-80 years, all pairwise year grouped differences were significantly different ($p < 0.05$). For ice off, except for 41-80 and over 80 years, and 11-20 and 21-40 years, all pairwise differences were significantly different from each other ($p < 0.05$).

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3.4 Case Study - Extreme Events

We chose a grid which contained at least 3 lakes to compare how the projections differ from the in situ observations on a year by year basis, to detect what in situ events the gridded models cannot capture. Hence, we chose a grid in Madison, Wisconsin, USA, where Lakes Wingra, Mendota, and Monona are located. We observed that the models captured the variation in in situ ice on days well most of the years (Figure 5). However, it is evident that in years when extreme values occur, the ISIMIP models cannot capture such extreme conditions. For example, in the last century, Lake Monona had 5 extreme events for ice off, where the lake thawed in January (orange lines on Figure 5). The models were not able to capture these extreme events. The same phenomenon was observed with Lake Mendota, where the extreme events were not within the range of the models. Not surprisingly, the models performed well when extreme events were infrequent, as evident from the time-series of ice on days where there were fewer extreme events.

4 Discussion

Predicting physical and biological lake responses to climate change will be critical for adaptation in the coming decades. In this study, we found that global process-based models of lake ice accurately captured the timing and duration of real-world observations of seasonal ice cover, often only inaccurate by between two and six days. The accuracy of the models was influenced by geographic region, with both latitude and longitude suggested as important predictors of accuracy. The physical characteristics of the lakes were also relevant for model accuracy, with ice phenology in larger and deeper lakes typically being more difficult to predict. The lake ice models were more effective at estimating long-term trends relative to short term change, suggesting that while predicting the timing of ice cover for a specific year may lead to inaccuracies, estimating patterns over multiple decades will be more reliable. There was no single lake model that was more effective at estimating patterns of lake ice, with individual lakes performing best in some years and worst in others, thus suggesting that an ensemble approach may be the most beneficial. While our findings highlight some discrepancies with in situ observations, we found evidence that modelling lake ice patterns can be an effective approach for estimating long-term trends in lake ice.

4.1 Predictability of lake ice

Geography mediated the predictability of lake ice patterns. Being able to predict climatological or biological responses across multiple countries and continents is certainly challenging because of the complex, region-specific differences in geography. Using an ensemble-model approach, such as we have done here, can be more effective at estimating climate patterns by reducing model-specific anomalies, i.e., abnormally large departures from other models (Semenov and Stratonovitch, 2010). However, averaging across models can reduce the ability to predict responses in regional conditions that specific models attempt to address. This may explain why the location of the lake was an important variable predicting the accuracy of lake models. Alternatively, the decrease in accuracy from lake models might be caused by a lower number of available in situ observations to compare. For example, RMSE increased markedly between -50 and 0° longitude, but these areas correspond with the Atlantic Ocean and have only few in situ observations. Latitude was also an important variable in determining model accuracy that could be explained by global patterns of temperature isotherms. We calculated the lowest RMSE (i.e., most accurate) between 50 and 65° latitude which reflects the higher density of lakes in northern latitudes and highest abundance of lakes currently experiencing intermittent ice cover (Sharma et al., 2019). Most lakes outside of this band are either permanently ice-free or permanently frozen, suggesting the lake models are effective at predicting the phenology of intermittent ice cover. While lake location plays an important role in determining the accuracy of models, the highest degree of accuracy is where most lakes are present.

Some of the more substantial differences between models were caused by extreme events. Extreme climate events are inherently difficult to predict and thus difficult to include in models (Easterling et al., 2000). Additionally, the global circulation models that are used in these lake models are intended to explore mean changes in climate over time (Taylor et

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Preprint. Discussion started: 9 February 2022

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al., 2012). While we are improving our ability to predict the frequency of extreme events over a select period of years (Sillmann et al., 2017; Hanlon et al., 2013), predicting the specific year an extreme event occurs in the future is not currently possible. This may explain why when a longer time series was used, the accuracy increased, as these high-variability events are averaged out. Some of the extreme events we observed that reduced model accuracy corresponded with local climate phenomenon. For instance, the El Niño Southern Oscillation (ENSO) can drive abnormally early ice-breakup dates in North America (Lopez et al. 2019). This pattern was supported by our models that inaccurately predicted ice off date as later than observed for lake Mendota during a particularly strong ENSO event in 1997-1998 and 2015-2016 (Figure 5). ENSO events have been attributed to several noticeably early break-ups for lakes in recent decades, such as 1972, 1982, and 1997, as well as an unusual lake ice on event 1930-1931 (Magee et al., 2016). Other teleconnection climate patterns can drive ice phenology including the North Atlantic Oscillation (NAO), which has been determined to be a significant driver of ice break up for Lake Baikal, Siberia (Livingstone, 2000; Lopez et al., 2019). Although we may be able to predict the effect of these large climate oscillations on lake ice patterns, predicting their occurrence beyond a year or two into the future remains a significant challenge (Park et al., 2018). Our ability to predict lake ice is thus only as accurate as our ability to predict future climate patterns.

4.2 Utility of lake ice models

The usability of lake models is largely determined by the purpose. Differences in models, scale, and time series can each play a significant role in the accuracy of outcomes. In our study, there was no model that provided evidence of superior performance, but inclusion of each was important at capturing variations in the relationship between climate and lake ice. An ensemble approach is preferable to account for this variability and while computationally intensive, increasing availability of resources and open-access software like Lake EnsembleR, are increasing the accessibility of this method (Moore et al., 2021). A common limitation of gridded climate data, like those used as inputs to the lake models investigated here, is the high spatial resolution averages variation at more localized scales (Liang et al., 2008; Fick and Hijmans, 2017). For example, the lake models have a resolution of ~55 km which can represent an average of many small lakes, a single lake, or a portion of a large lake. The accuracy of predicting a single lake is thus related to the number of lakes shared in the predicted area, particularly those with similar characteristics. Incorporating regional climate models (RCMs) can improve spatial resolution (e.g., < 55 km) and more accurately predict localized climate patterns (Liang et al., 2008; Di Luca et al., 2013), but availability of these models across the Northern Hemisphere are limited. Time frame was an important variable in determining the accuracy of models and as explained above this is largely driven by averaging climate anomalies over time. For users looking to predict the lake conditions for a specific lake in a given year, there is a relatively low likelihood of correctly selecting the exact dates of ice on and ice off. We caution future users estimating specific lake responses to be wary of the effects of extreme events, local heterogeneity, and accuracy in regions without observational data. However, predictions over a larger region and longer time period, model accuracy is likely to be accurate within a few days. Therefore, we recommend using these models to quantify trends in ice loss, but not for actual estimates of ice on and off dates.

5. Conclusions

The lake models presented in this study are an invaluable tool in efforts to understand and manage the loss of lake ice in the future. We suggest the following four recommendations when using these data: i) consider the relationship between lake ice and extreme climate events, ii) be cautious with predictions for regions currently without in situ representation, iii) when possible, use ensemble model approaches to reduce variability in predictions, and iv) estimate long-term trends rather than specific lake responses. Using these recommendations, we found support that lake ice is declining in both the modelled and in situ data. For ice on, modelled estimates were often more conservative than in situ observations which predicted a later ice on date. In fact, the real-world observations had later ice on and earlier ice off dates than any of the estimates from all three of the RCP scenarios. These findings are largely confirmatory of the many studies forecasting the loss of lake ice (Sharma et al., 2019; Grant et al., 2021; Li et al., 2021) and suggests that true loss of lake ice may be even greater than forecasted by climate change scenarios. Continued development and integration of tools, such as process-based models, remote-sensing, and broader in situ observations, coupled with improved understanding of responses to climate will be critical (Sharma et al., 2020) as we continue to experience the consequences of climate change in the coming decades.

Acknowledgments

This work was supported by a UKRI Natural Environment Research Council (NERC) Independent Research Fellowship awarded to RIW [grant number NE/T011246/1]. For their roles in producing, coordinating, and making available the ISIMIP climate scenarios, we acknowledge the support of the ISIMIP cross sectoral science team.

Author Contribution

All the authors contributed to the development, writing, and revision of the manuscript. MAI, AF, RIW, SS contributed to the methodology, data curation, and visualization of the results. MAI and AF performed the formal analysis and validation. SS led funding acquisition and supervised the project.

Competing Interest

The authors declare they have no competing interests.

Data Availability

The data for the ice projections from different lake models and representative concentration pathways are available at the website for Inter-Sectoral Impact Model Intercomparison Project (ISIMIP) https://esg.pik-potsdam.de/.

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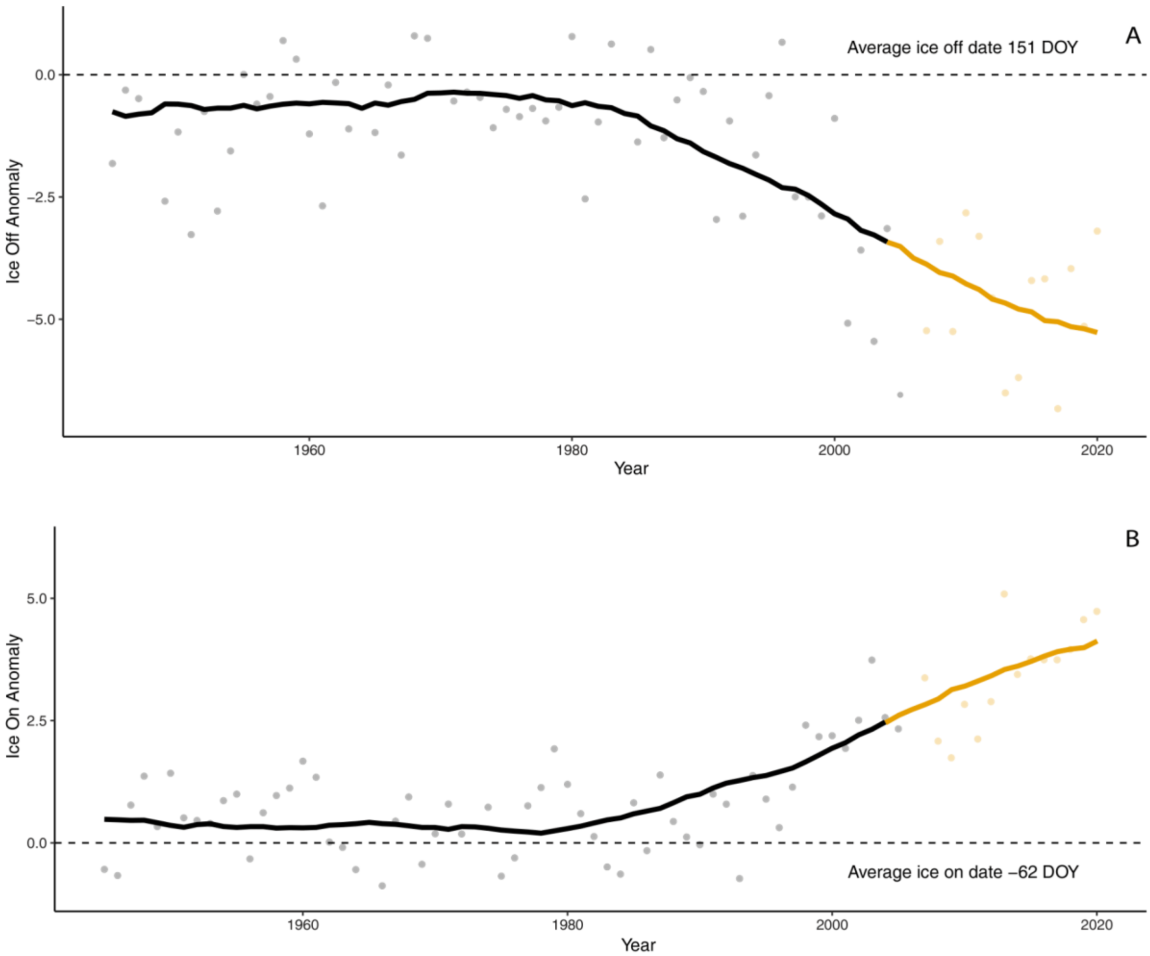

460 **Figure 1: Ice off (A) and ice on (B) anomaly in the Northern Hemisphere.** The orange color represents ice phenology predictions under RCP 6.0. We used the years 1901-1930 as an average baseline. The anomaly is defined as the day difference in average ice on/off for a year and the average baseline. We define DOY (Day Of Year) as the number of days from January 1st, with January 1st being 0, days after January 1st being positive and days before January 1st being negative.

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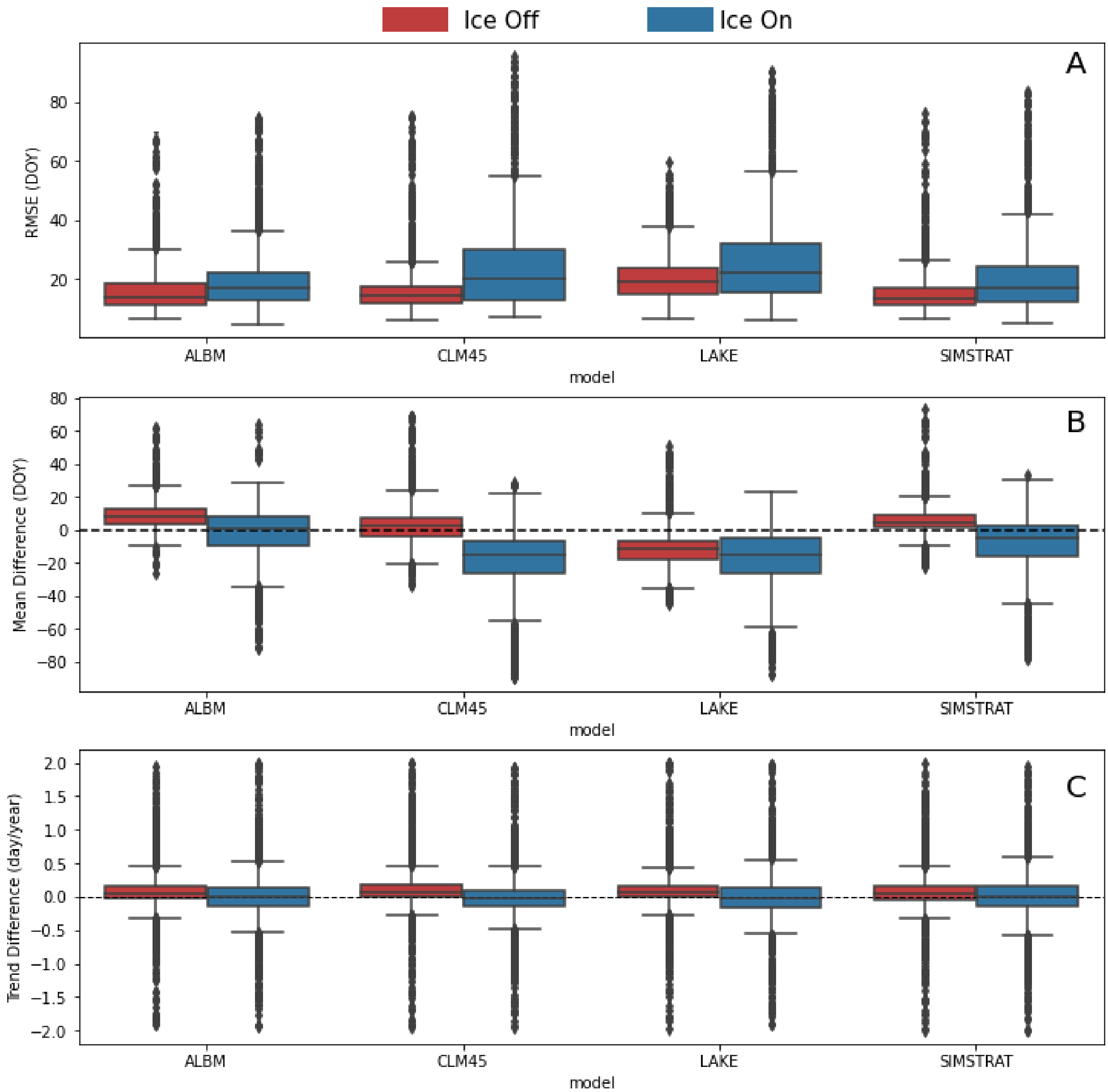

Figure 2: Difference in A) RMSE (DOY), B) Mean Difference (DOY), and C) Trend Difference (DOY) for 4 process-based lake models compared to in situ observations. We used grids where we had in situ observations and compared how the ISIMIP models performed relative to the observations, using the metrics of RMSE (DOY), Means (DOY), and Trends (day/year). For panel A, the differences between RMSE for the models were significant, except between ALBM and CLM45 and between ALBM and SIMSTRAT. For panel C, there was no significant difference among the models for both ice on and ice off. We define DOY (Day Of Year) as the number of days from January 1st, with January 1st being 0, days after January 1st being positive and days before January 1st being negative.

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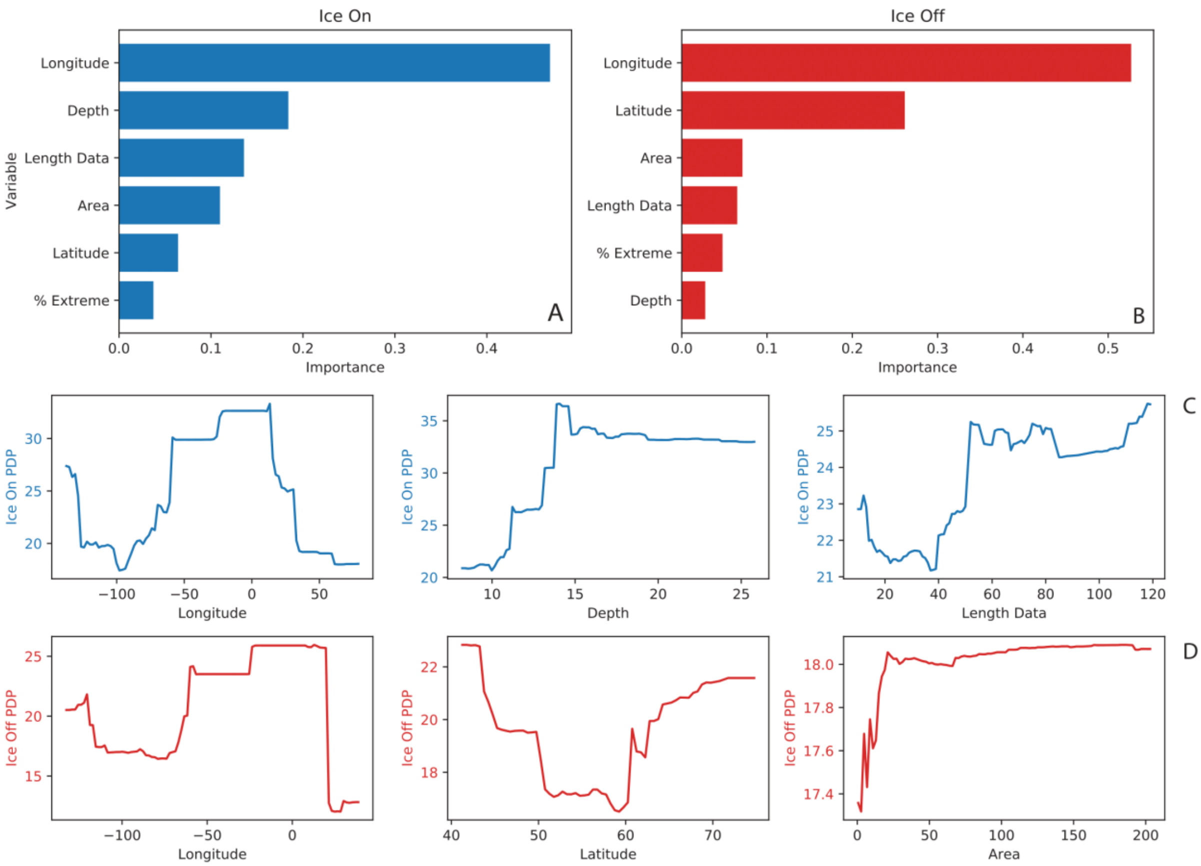

470 **Figure 3: Drivers of differences in RMSE.** We used random forests to identify the important drivers affecting RMSE of ice on (A) and ice off (B). Rows (C and D) represents the partial dependence plots for the 3 most important drivers for ice on (C) and ice on (D). Depth indicates the average depth of the lakes in the grid. Area indicates the average area of the lakes in the grid. 'Length Data' represents the average length of time series of lakes in the grid, and '% Extreme' represents the percentage of extreme events observed in the lakes in that grid, over the time series.

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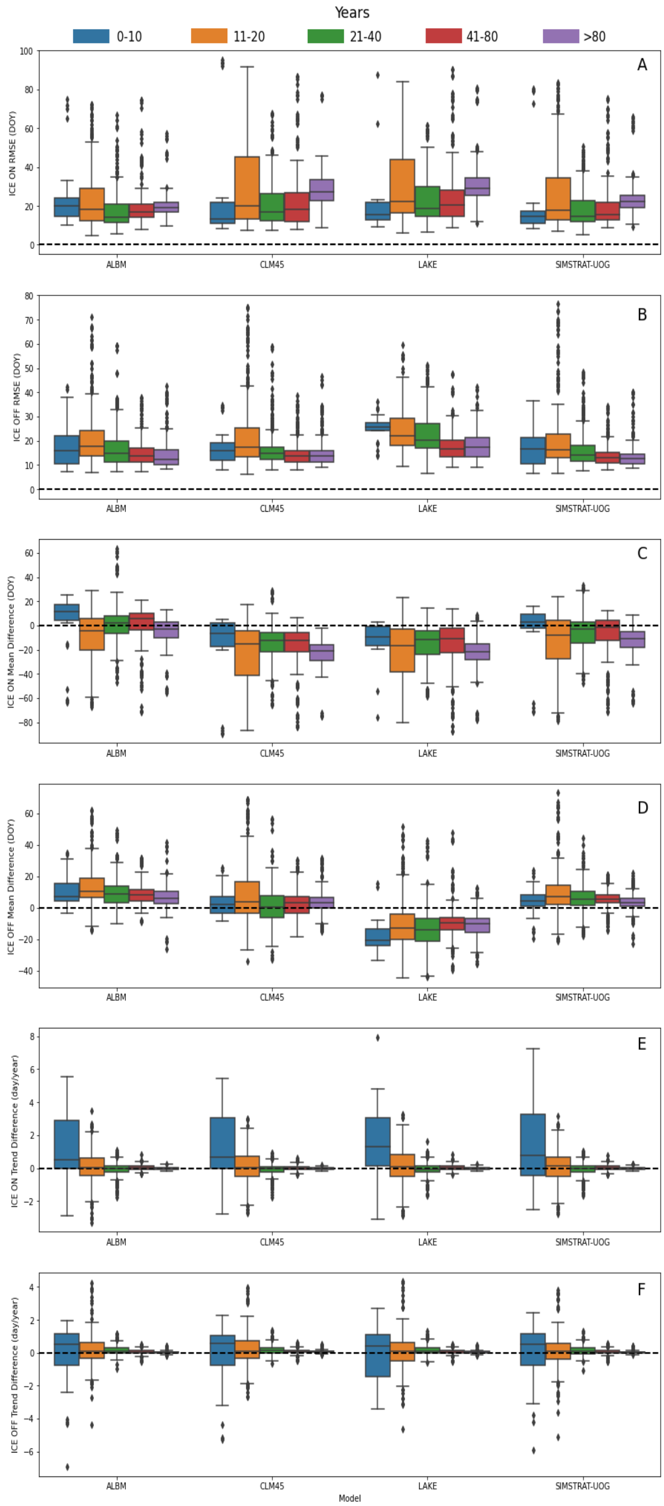
475 

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Figure 4: Effect of length of time series on RMSE, Mean Difference, and Trend Difference. We subset the data into bins of 0-10 years, 11- 20 years, 21-40 years, 41-80 years, and over 80 years. For the grouped years, there were no significant differences between the groups when the length of the time series was over 40 years ($p > 0.05$), and no significant difference between 0-10 and 21-40 years (post hoc test, $p > 0.05$).

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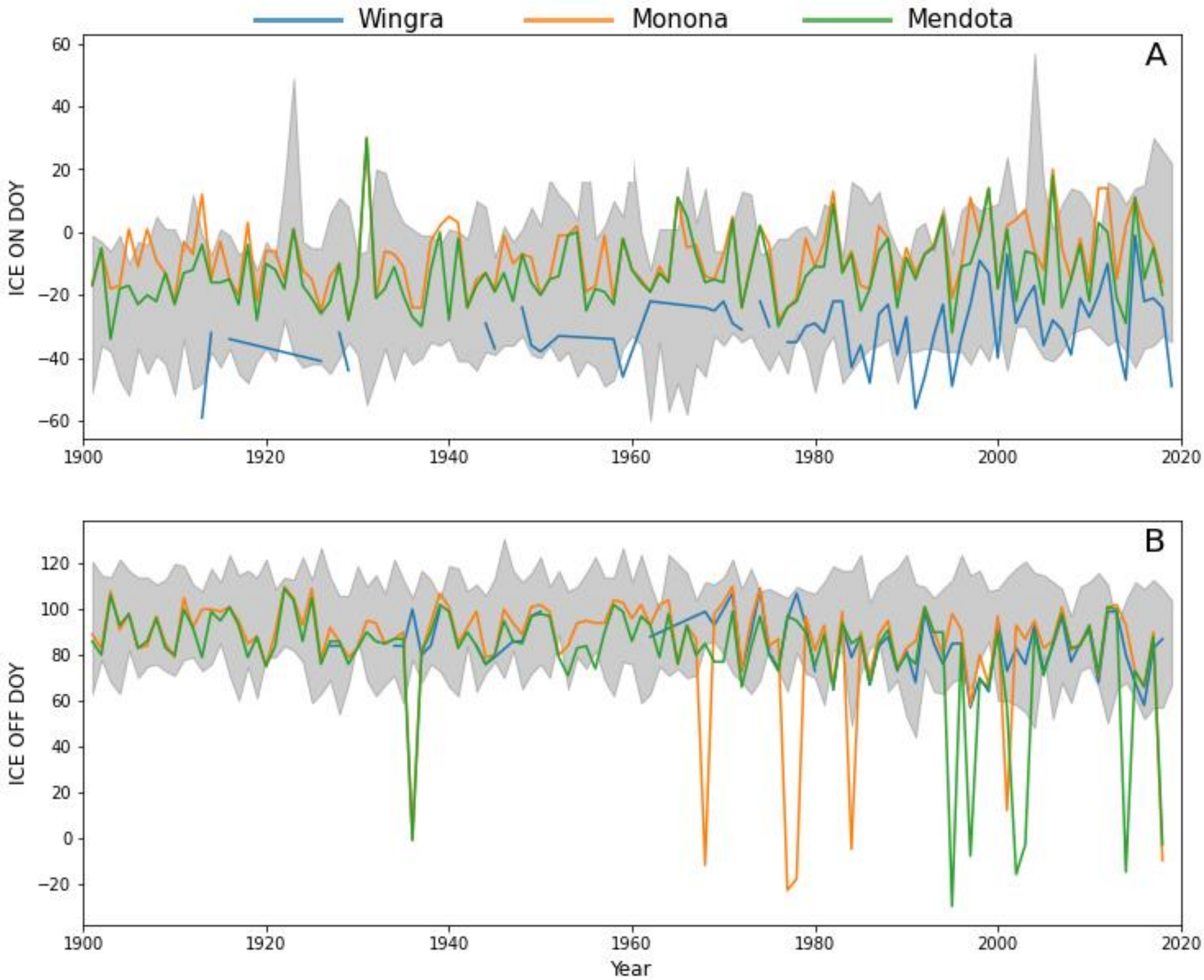

Figure 5: Time-series graphs of ice on (A) and ice off (B) for Lakes Wingra, Monona, Mendota and ISIMIP models in the grid. We plotted the in situ observational time series of the 3 lakes and the ISIMIP modelled data for the grid cell containing these lakes. The coloured lines represent the in situ observations for the three lakes and the shaded regions represent the range of values obtained from the
485 ISIMIP models.