

Reply to RC1

Note: the comments and authors' replies are in black and blue font, respectively. All changes in the revised manuscript are highlighted in yellow.

This manuscript had two major goals. First to create an improved algorithm for extracting breakup and freeze-up dates using microwave-based temperature brightness data from satellites on a shallow, and vegetated lake. And second, to re-construct a long ice phenology timeseries extending back in time before the availability of satellite-based estimates. The novelty of the study appeared to be the development of the DMTT algorithm to extract freeze-up and break-up dates. The DMTT algorithm appears to be better suited for mixed pixels more commonly associated with lakes with vegetated cover or complex shorelines.

The authors could use more clarity in their introduction and methods sections, specifically to both highlight the novelty of the study, summarize what has been done in the past, and differentiate better the different types of data. Regarding novelty, I think the authors should spend more time comparing the DMTT and MTT (e.g. expanding more on the improvements made). I believe this will help readers understand which algorithm to use given their own lake data. Further, the authors state that their goal was to understand shallow lakes with complex shorelines and mixed pixels, however they chose 5 pixels from the CETB dataset which only contains pixels that are mostly water. Also, the pixels are not fine resolution enough to capture the complex shoreline. The authors could spend more time justifying the use of this type of data for ice phenology research, especially on shallow lakes with complex shorelines/vegetation, or de-emphasize the mixed pixels and focus more on the shallow lake aspect. In the same vein, I suggest the authors spend some time in their introduction qualifying why microwave-based methods are more accurate or better than optical based methods. One suggestion would be to discuss if microwave data can improve upon the errors associated with missing the freeze-up or break-up dates due to cloudy pixels, which is ~5 days for the MODIS method (Zhang and Pavelsky, 2019) or whether microwave data better corresponds to in-situ data, if available. Finally, the authors could more clearly differentiate what data were used and where they came from. I liked the idea of Figure 2, but I found it hard to follow. I would suggest starting with raw data on the left and moving to more derived products on the right (or the same suggestion but top to bottom). All external validation data should be clearly marked versus the data use for testing and training in the RF model. I put more detailed comments about clarity throughout the

methods section.

Reply: Thank you very much for your constructive comments on our manuscript. We have addressed each of your concerns and please see our response to the point of view listed above:

(1) We have thoroughly restructured the Introduction (lines 23-57) to better articulate the importance of studying ice phenology in shallow, vegetated lakes and to emphasize the advantages of passive microwave remote sensing over other methods.

(2) The data description (Section 3.1) and methodological details (Section 3.2) have been revised for clarity. Each dataset's purpose and application within our study are now explicitly defined, underscoring the rationale behind our choices and their relevance to the study objectives. We have also introduced a new section (4.1 Algorithm evaluation) that not only compares our results with optical remote sensing outcomes but also with MTT algorithm outputs and in-situ observations, demonstrating the robustness and superiority of the DMTT algorithm.

(3) We provide comprehensive justifications for selecting predominantly water pixels, highlighting their relevance in capturing valuable ice phenology insights even in mixed pixels (detailed response in specific comments 20-23). This selection is crucial given the complex shorelines and vegetated cover of Lake Ulansu, demonstrating why the DMTT algorithm is particularly suitable for our study conditions. Furthermore, in Appendix F, we have included examples of similar "Ω"-type brightness temperature series from other lakes to illustrate the broader applicability and current research gaps in lake ice phenology under algorithm constraints.

(4) We have clarified the advantages of using passive microwave remote sensing over optical methods in our study. The passive microwave data, which cover a more extended period and offer daily revisit capabilities, were instrumental in reconstructing the ice phenology from 1979 to 2023. This long-term dataset was compared against the shorter-term optical remote sensing data from MODIS, Landsat and Sentinel-2 from 2000 to validate our findings, as detailed in the revised Section 3.1.2 Optical satellite data.

(5) Figure 2 has been redesigned for improved clarity. It now presents a logical progression from raw data to processed outputs in a top-to-bottom format, making it easier for readers to understand the data workflow used in our study. This figure effectively delineates the types of data used for training and testing in the random forest model versus those used for external validation.

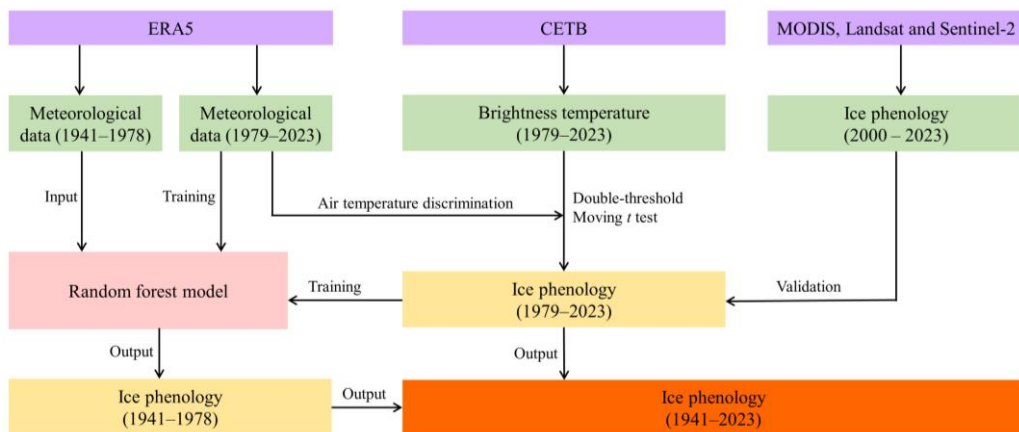


Figure 2: Reconstruction of the ice phenology of Lake Ulansu (1941–2023) based on ERA5, CETB, and optical satellite data via the double-threshold moving t test algorithm and random forest model.

Specific comments:

1. Line 10 is this multi-source? Can you be more specific? Is this ERA5 data or other types of data?

Reply: We utilized Calibrated Enhanced-Resolution Passive Microwave Daily EASE-Grid 2.0 Brightness Temperature (CETB) data. These data were sourced from the SMMR on the Nimbus 7 satellite; the SSM/I on the DMSP-F08, -F10, -F11, -F13, and -F14 satellites; and the SSMIS on the DMSP-F16 satellite. Meteorological data were obtained from ERA5. To clarify the abstract, it has been revised to "*To address this challenge, a new double-threshold moving t test (DMTT) algorithm, which uses SMMR and SSM/I-SSMIS sensor-derived brightness temperature data at a 3.125-km resolution and long-term ERA5 data, was applied to capture the ice phenology of Lake Ulansu from 1979 to 2023.*"

2. Line 23 consider “global lake ice loss is a prominent feature associated with climate change” or simplifying this beginning sentence so it is in more active voice.

Reply: Revised accordingly.

3. Line 25 what do you mean by ecological balance?

Reply: We have revised the sentence: "*Lake ice regulates water temperature, light availability, and nutrient circulation, which are crucial for the ecological environment (Latifovic and Pouliot, 2007; Wu et al., 2022).*"

4. Line 26 can you elaborate on how ice cover impacts the momentum and mass exchange between the atmosphere and water?

Reply: Ice cover in lakes plays a crucial role in regulating the exchange of momentum and mass between

the atmosphere and the water body. The following is an elaboration of this process:

- (1) Momentum exchange: The presence of ice on the lake surface acts as a barrier, altering momentum exchange by reducing the direct transfer of wind energy to the water. This results in lower surface stress and reduced mixing within the water column. The momentum from the wind is partially transferred to the ice, causing it to drift, but the movement and mixing of the water below the ice are minimal compared with those in ice-free conditions. In the absence of ice, the wind directly impacts the water surface, creating waves and turbulence, which enhances the mixing of the water column. This mixing is critical for the distribution of heat, nutrients, and other materials throughout the water body (Kirillin et al., 2012; Leppäranta et al., 2023).
- (2) Mass exchange: Ice cover reduces evaporation rates, limiting the transfer of water vapor from the lake to the atmosphere. This affects local humidity levels and can influence weather patterns. Additionally, ice can trap gases such as methane and carbon dioxide beneath it, altering gas exchange dynamics and impacting the lake's biogeochemical cycles (Zhao et al., 2022; Li and Xue, 2021).

We appreciate this opportunity to elaborate on these processes, enhancing our understanding of the broader environmental impacts of lake ice cover. Given the extensive revisions made to the Introduction of our manuscript to enhance clarity and focus, this detailed discussion of ice cover impacts on momentum and mass exchange was not included in the main text to maintain coherence and relevance to the primary research aims.

5. Line 28 see also Sharma et al. 2019, consider wording similar to: Many studies have evaluated lake ice phenology trends in the northern hemisphere, but shallow and vegetated lakes remain largely unexplored due to their lack of observational data

Sharma, Sapna, Kevin Blagrove, John J. Magnuson, Catherine M. O'Reilly, Samantha Oliver, Ryan D. Batt, Madeline R. Magee, et al. 2019. "Widespread Loss of Lake Ice around the Northern Hemisphere in a Warming World." *Nature Climate Change* 9 (3): 227–31. <https://doi.org/10.1038/s41558-018-0393-5>.

Reply: We rephrased this sentence to "*Many studies have evaluated lake ice phenology trends in the Northern Hemisphere (Mishra et al., 2011; Sharma et al., 2019; Woolway et al., 2020), but shallow and vegetated lakes remain largely unexplored owing to their lack of long-term observational data.*"

6. Line 32 The sentence "shallow lakes are more sensitive to climate change than deep lakes because of, because of their potential ecological effects on algal blooms" does not seem like a complete sentence. Are you trying to say that the fact that these lakes get algal blooms mean that they are more

sensitive to climate change. Lake ice and ice formation seem to clearly stem from climate change sensitivity, but I feel that algal bloom formation is related to several factors including temperature, ice, nutrients, etc.

Reply: Here, the revised version addresses your concerns: "*These lakes are more sensitive to climate change than deep lakes are because of their low heat capacity (Ambrosetti and Barbanti, 1999), which makes them more responsive to temperature fluctuations. A shortened ice-covered season leads to a longer period of open water, enhancing conditions for algal bloom growth and potentially causing ecological imbalances (Duan et al., 2012).*"

7. Line 34 what do you mean by microlevel, microscopic, lake-specific, etc.?

Reply: In the context of our manuscript, "microlevel" interactions refer to small-scale, detailed interactions within lake ecosystems that encompass physical and biological processes.

To make the text clearer, we revised it to "*Ice phenology data from such shallow lakes are crucial for understanding how temperature fluctuations influence water stratification, nutrient availability, and the biological rhythms of aquatic organisms (Sharma et al., 2021; Smits et al., 2021).*"

8. Line 37 Consider Hampton et al. 2017 (or citations within) if you want to make a broad statement of the need more lake ice research irrespective of shallow lakes, otherwise make this statement more explicitly about shallow lakes

Hampton, Stephanie E., Aaron W. E. Galloway, Stephen M. Powers, Ted Ozersky, Kara H. Woo, Ryan D. Batt, Stephanie G. Labou, et al. 2017. "Ecology under Lake Ice." Edited by James Grover. *Ecology Letters* 20 (1): 98–111. <https://doi.org/10.1111/ele.12699>.

Reply: Revised accordingly.

9. Line 47 what is the temporal resolution?

Reply: We added this information to the Introduction: "*Active microwave remote sensing is utilized primarily for extracting ice phenology data from large water bodies because of its relatively low (> 10 days) temporal resolution (Antonova et al., 2016; Howell et al., 2009).*"

10. Line 57 consider rewording the sentence that starts with "in addition..." This sentence marks an important transition from your text about creating phenology records using satellite data and creating a forecasting/back casting model using meteorological data. Here maybe you could emphasize past work

using satellite (optical/microwave) as training data to create longer term time series

Reply: To make the text clearer, change it to *"In addition, if long-term lake ice phenology records are desired, satellite remote sensing can also provide training datasets for machine learning (Wu et al., 2021; Xu et al., 2024). For example, Ruan et al. (2020) presented a practical machine learning application in which a random forest model was used to forecast the ice phenology of lakes on the Tibetan Plateau until 2099. The ice phenology history derived from passive microwave remote sensing and CMIP6 meteorological data was employed here as inputs. The success of this application largely depends on the quality of the training data, which requires not only accuracy but also a long temporal record that captures the variability of environmental conditions. To ensure the robustness of the model, it is critical to integrate diverse meteorological factors, such as air temperature, wind speed, and precipitation, along with ice phenology data, as these factors significantly influence lake ice. Furthermore, developing effective machine learning models that can address the complexities of lakes with various surface characteristics is essential."*

11. Line 68 using which data?

Reply: The original text has been modified to *"A new algorithm was developed to classify the ice and water states on the lake surface in brightness temperature data from the SMMR and SSM/I-SSMIS sensors for the period 1979–2023."*

12. Line 70 using the created data in step one as training data?

Reply: Yes. To make the text clearer, change it to *"(2) A random forest model was trained using the results in step (1) to reconstruct the ice phenology from 1941 to 1978."*

13. Line 80 Is there a citation associated with the evaporation and precipitation data?

Reply: Two corresponding citations have been added. See details on lines 84-86.

14. Line 100 Am I correct that the phenology record using CETB was not used in the training of the random forest model, only the phenology record derived from optical satellite data?

Reply: Ice phenology data from 1979 to 2023, derived from CETB data, were used to train the random forest model. The ice phenology data obtained from optical satellite data (2000 to 2023) were used to validate the results derived from the brightness temperature data (1979 to 2023) but were not used for training the random forest model. We have made the necessary changes in the manuscript to reflect this

clarification. See details on line 106.

15. Line 100 meteorological data from ERA5?

Reply: Yes, meteorological data from ERA5 for the period of 1979 to 2023 were used to train the random forest model. Additionally, ERA5 data for the period from 1941 to 1978 were used to calculate historical ice phenology data. We have clarified this in the manuscript to avoid any confusion. See details on lines 107-109.

16. Line 113 What is the spatial resolution

Reply: We added spatial resolution information in Section 3.3.1, "*The CETB data were obtained from various satellite sensors with coarse spatial resolutions (~25 km), including SMMR on Nimbus 7, SSM/I and SSMIS on the DMSP satellite series, and AMSR-E on Aqua (Brodzik et al., 2016).*"

17. Line 125 the ice phenology data originated from the cloud bitmask in the state_1km product of MODIS? How does that reduce the influence of clouds?

Reply: Huo et al. (2022) calculated the ice phenology data for Lake Ulansu after 2000 via optical satellite data, specifically the red band reflectances from the MOD09GQ and MYD09GQ datasets, cloud information from the state_1 km_1 parameter in the MOD09GA and MYD09GA datasets, and the Landsat and Sentinel-2 datasets. The temporal resolution of both MOD and MYD is one day, with images taken at 10:30 AM and 1:30 PM local time, respectively. To fill real pixels under clouds, the higher temporal resolution of the MODIS products was utilized by merging MOD09GQ from the Terra satellite with MYD09GQ from the Aqua satellite. The details are as follows:

The first step to fill the cloud-covered pixels is shown in Equation (R1), where P denotes the pixels and the output is the pixel type (water/ice) of the output satellite. It is divided into two cases: (1) if Aqua data are identified as water (ice) at pixel A , a pixel is defined as water (ice); (2) if Aqua data are identified as clouds at pixel A and the Terra satellite is identified as water (ice) at pixel A , a pixel is defined as water (ice).

$$P_{(A,output)} = \begin{cases} \text{water/ice,} & \text{if } P_{(A,Aqua)} = \text{water/ice} \\ \text{water/ice,} & \text{if } P_{(A,Aqua)} = \text{cloud AND } P_{(A,Terra)} = \text{water/ice} \end{cases} \quad (R1)$$

The second step uses the temporal continuity principle to associate the type of A pixel on day t with the same pixel on days $t - 1$ and $t + 1$ (Equation R2). The detail is that if the A pixel on day t is a cloud pixel

and is discriminated as water (ice) on days $t - 1$ and $t + 1$, then the pixel on day t is defined as water (ice).

The formula is as follows:

$$P_{(A,t)} = \text{water/ice}, \quad \text{if } P_{(A,t-1)} = P_{(A,t+1)} = \text{water/ice} \quad (\text{R2})$$

Some cloud pixels that exist after Equation (R2) is applied are further calculated on the basis of the five days of temporal continuity. As shown in Equation (R3), there are two cases: (1) if the A pixel is a cloud on days $t - 1$ and t and is water (ice) on days $t - 2$ and $t + 1$, then the A pixel is defined as water (ice) on days $t - 1$ and t ; (2) if the A pixel is a cloud on days t and $t + 1$ and is water (ice) on days $t - 1$ and $t + 2$, then the A pixel is defined as water (ice) on days t and $t + 1$.

$$\begin{cases} P_{(A,t)} = P_{(A,t-1)} = \text{water/ice}, & \text{if } P_{(A,t-2)} = P_{(A,t+1)} = \text{water/ice} \\ P_{(A,t)} = P_{(A,t+1)} = \text{water/ice}, & \text{if } P_{(A,t+2)} = P_{(A,t-1)} = \text{water/ice} \end{cases} \quad (\text{R3})$$

Based on the above three steps, Huo et al. (2022) reduced the average cloud coverage from over 30% to 6.4%. This study uses the ice phenology data for Lake Ulansu calculated by Huo et al. (2022) to validate the passive microwave remote sensing results. Therefore, the detailed cloud removal process is not extensively explained in the manuscript. To ensure logical consistency in Section 3.1.2, *"These optical satellite data include red band reflectances from the MOD09GQ and MYD09GQ datasets, cloud information from the state_1 km_1 parameter of the MOD09GA and MYD09GA datasets, and the Landsat and Sentinel-2 datasets. The single-band threshold method classifies red band reflectances into water and ice pixels. Compared with higher spatial resolution Landsat and Sentinel-2 datasets, the dynamic threshold method aims to determine the optimal threshold for distinguishing ice and water pixels (Zhang and Pavelsky, 2019). Additionally, the spatiotemporal continuity of MODIS datasets is used to fill in real pixels under clouds, resulting in more accurate pixel classification."*

18. Line 131 Which part of Sentinel-2 and Landsat did you use to create your threshold? Can you elaborate more on the specifics of this method (e.g. Fmask on Landsat, and a threshold of X in the MODIS red band reflectance from the 250 m product)

Reply: The red band reflectances from MOD09GQ and MYD09GQ were used to differentiate between ice and water pixels (Zhang and Pavelsky, 2019), specifically via Equation R4:

$$P = \begin{cases} \text{ice}, & \text{if Band 1} \geq a \\ \text{water}, & \text{if Band 1} < a \end{cases} \quad (\text{R4})$$

where Band 1 represents the reflectance of the red band and a represents the threshold to distinguish between water and ice.

Then, the Normalized Difference Snow Index (NDSI) formula was subsequently applied to Landsat and Sentinel-2 images to distinguish between ice and water pixels:

$$NDSI = \frac{\text{Band 2} - \text{Band 5}}{\text{Band 2} + \text{Band 5}} \quad (\text{R5})$$

where Band 2 and Band 5 represent the reflectances of the green and shortwave infrared bands, respectively, in the Landsat and Sentinel-2 products. $NDSI = 0.4$ was selected as the threshold (Cai et al., 2019). The vector boundary of water/ice was extracted via manual visual judgment, and the water/ice coverage in the Landsat/Sentinel-2 images was calculated.

Finally, the dynamic threshold method was employed to constantly modify the threshold a to change the water/ice classification results of the MOD09GQ/MYD09GQ dataset and compared with the water/ice coverage areas of the Landsat and Sentinel-2 products with high spatial resolutions to find the optimal threshold a .

Given that this section is not the core focus of our study, these formulas are not presented in Section 3.1.2.

19. Line 135 Did you use the phenology record directly from Huo et al. 2022? If so, then I would put that citation further up

Reply: This study directly uses the results of Huo et al. (2022) to validate the ice phenology results derived from brightness temperature (T_b) data. To make the purpose of Section 3.1.2 clearer, it is now stated in the first sentence of the section "*In this study, we use ice phenology data for Lake Ulansu from 2000 to 2023 obtained from optical satellites by Huo et al. (2022) to validate the ice phenology results derived from T_b data.*"

20. Line 179: Did you mean “we could not use the omega-shaped analysis for this study because the “w” shape violates that method”? The sentence as it currently reads is a little vague as to why the omega series are not available

Reply: The primary issue is the W-shaped variation in the brightness temperature (T_b) series at Lake Ulansu, which is significantly influenced by mixed pixels, unlike the pure water pixels observed in larger lakes such as Great Bear Lake and Qinghai Lake, which display a clear Ω -shaped T_b series (Fig. R1).

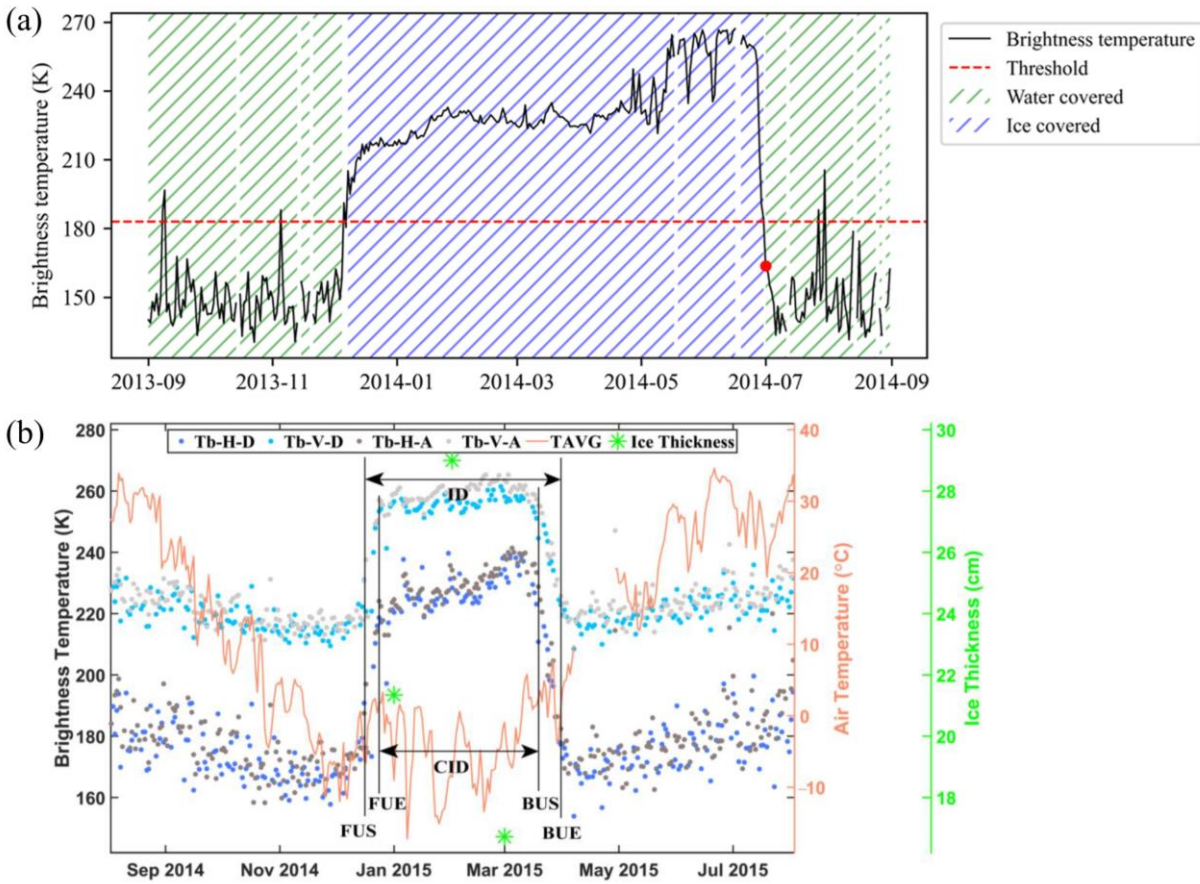


Figure R1: Example of an Ω -shaped T_b series in a large lake. (a): Great Bear Lake (Cai et al., 2022). (b): Qinghai Lake (Su et al., 2021).

The specific challenges presented by Lake Ulansu's T_b series are as follows:

- (1) Land influence: Land areas, with their lower heat capacity than water does, respond more quickly to air temperature fluctuations. This rapid response causes significant changes in surface temperature, leading to greater fluctuations in the T_b series (Munn and Richards, 1963; Wilheit et al., 1972).
- (2) Reduced T_b changes: At the critical moments of freezing and melting, the T_b changes in mixed pixels are less pronounced ($< 20K$) than those in pure pixels ($> 50K$, Fig. R1), necessitating more precise threshold settings for correct classification.
- (3) Increased abrupt change points: The variability in T_b due to the land response to air temperature increases the number of abrupt change points (ACPs) detected by the moving t test (MTT) algorithm, leading to potential misclassification of ice and water.
- (4) Necessity for dual thresholds: Pure water pixels exhibit stable changes in T_b , allowing the use of a single threshold to calculate freeze-up start and break-up end dates. In contrast, the varying surface temperature and emissivity in mixed pixels require separate thresholds for accurate classification.

Owing to these complexities, the Ω -shaped analysis method is not applicable. To address this, we

developed a double-threshold moving t test (DMTT) algorithm to extract ice phenology from the W-shaped T_b series, accommodating the mixed pixel conditions of Lake Ulansu.

Revised manuscript text *"In this study, the ice phenology from 1979 to 2023 was determined by the brightness temperature (T_b) of the lake surface because T_b changes considerably when a phase change occurs on the lake water surface (Su et al., 2021), providing a clear reference for determining the onset and end of the ice period. However, owing to the complex shape of the Lake Ulansu shoreline, which is characterized by its narrow form, pixels encompass not only water but also aquatic vegetation and land. As a result, five T_b grids with a proportion of lake water greater than 0.70 were selected to represent the status of the lake surface (Fig. 1b). Figure 3a shows the annual variation in T_b for each grid of each year as blue dashed lines, with the blue solid line showing the average for all grids during 1979–2023 and the solid red line depicting the average air temperature. The annual variation in the T_b of Lake Ulansu exhibited a typical 'W' shape (Fig. 3a). This is different from what is observed for large lakes with only water surfaces where T_b is typically a pure pixel, resulting in a line with an 'Ω' shape (Cai et al., 2022; Su et al., 2021). Compared with those of pure pixels, the mixed pixels of Lake Ulansu lead to inconsistent changes in surface temperature and emissivity, complicating the T_b series. To accurately determine the ice phenology, it is necessary to precisely establish different thresholds for the transition between water and ice. Thus, previous methods to address the Ω-shaped T_b series are not available in this study, and a double-threshold moving t test (DMTT) algorithm was developed to extract the ice phenology from the W-shaped T_b series."*

21. Line 180: Can you use this algorithm from all W-shaped series? How common is W-shaped series?

Reply: In this study, we focused exclusively on Lake Ulansu, which exhibited mixed pixels and a W-shaped T_b series due to its complex shoreline and seasonal freeze–thaw patterns. This W-shape is characteristic of lakes with significant seasonal dynamics and mixed land–water elements within the observed pixels.

To further validate our findings and the universality of the W-shaped T_b series beyond Lake Ulansu, we recently processed four additional lakes that exhibited similar seasonal characteristics (Fig. R2). These lakes, such as Lake Ulansu, feature mixed pixels where the T_b series is influenced by both water bodies and surrounding land. These additional studies underscore that W-shaped T_b series are indeed common in seasonally freezing lakes characterized by mixed pixels. Moving forward, we plan to enhance the DMTT algorithm further, aiming to expand its utility to a broader range of small- and medium-sized lakes globally. This advancement will provide deeper insights into the ice phenology of lakes under the influence of

climate change, particularly for periods and regions where high-resolution optical satellite data are not available. Figure R2 has been added to Appendix F of our manuscript, and future research directions are detailed on lines 472-475.

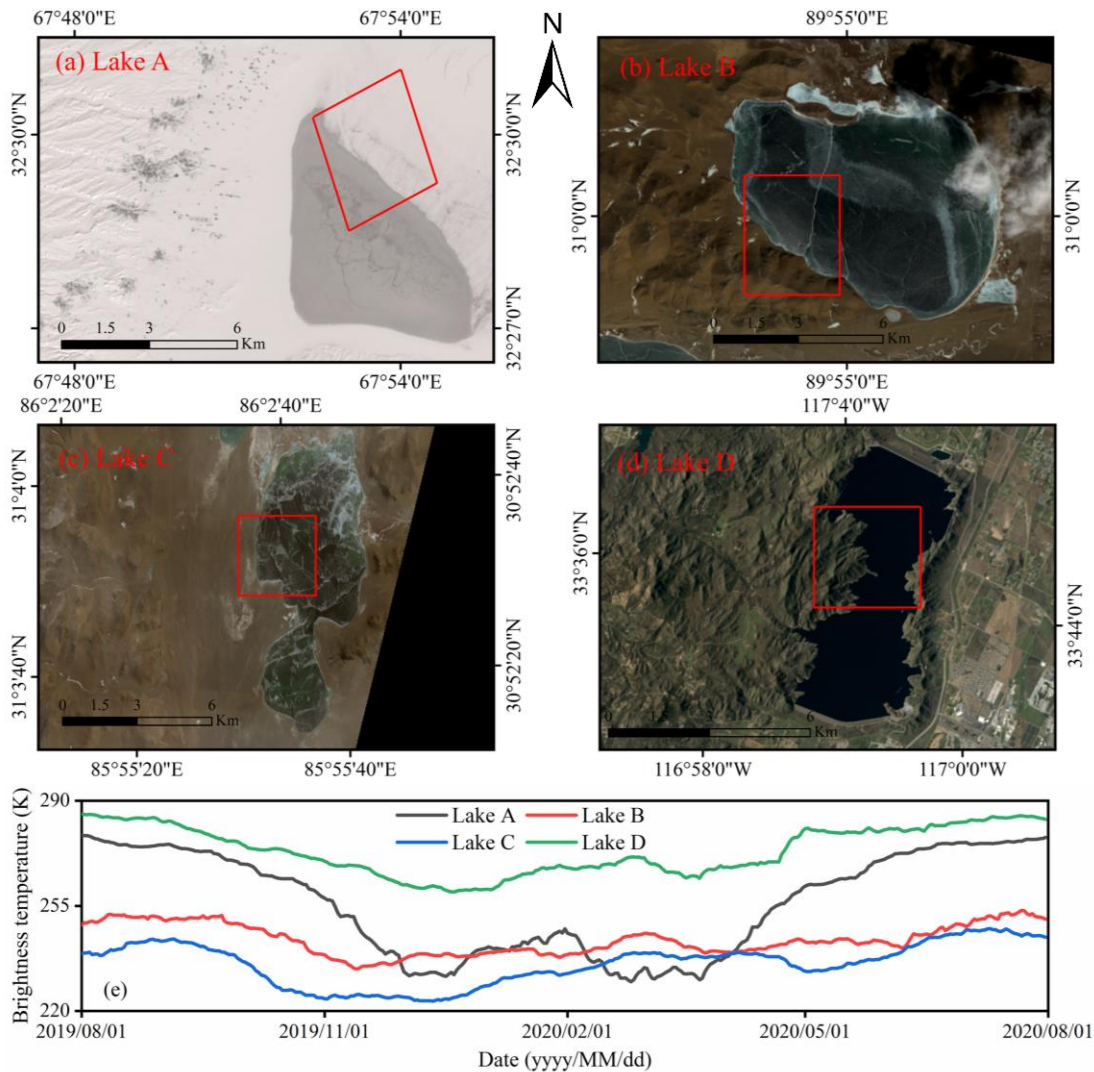


Figure R2: (a-d) Landsat 8 images of Lake A, Lake B, Lake C, and Lake D, areas within red rectangles where mixed brightness temperature pixels were analyzed. (e) Brightness temperature time series from August 1, 2019, to August 1, 2020, for each lake.

22. Line 190: I would add more information here about how your algorithm is different from the MTT since I feel like this is where the novelty of the study lies. Much of that information is in the appendices, and I would move that information into the main manuscript.

Reply: We have relocated the detailed comparison, previously found in the appendices, into the main body of the manuscript (Section 4.1 Algorithm evaluation). This adjustment ensures that the enhancements introduced by the DMTT are immediately apparent.

23. Line 193: How complex are the mixed pixels? The five that you show were mostly water and not near the edge. Do you still expect these pixels to be mixed?

Reply: Despite the selection of five pixels with a high proportion of water area, these pixels are still considered mixed because there are no pure water pixels within Lake Ulansu. The primary reason for selecting pixels with larger water areas is to minimize the influence of the land surface brightness temperature (T_b) and achieve more accurate ice phenology results for Lake Ulansu. These five pixels are located primarily in the central area of the lake where the water depth is relatively consistent, thus reducing the effects of uneven ice formation due to depth variation.

In previous studies that utilized satellite data to analyze lakes, a buffer zone was often established along the lake edge to avoid pixel contamination and ensure the quality of pure pixels (Cai et al., 2022; Giroux-Bougard et al., 2023; Heinilä et al., 2021; Korver et al., 2024; Kuluwan et al., 2023). However, Lake Ulansu has an elongated shoreline, and despite some pixels having a high proportion of water area, all pixels within the lake are subject to contamination by aquatic vegetation or land surfaces.

In this study, we used Calibrated Enhanced-Resolution Passive Microwave Daily EASE-Grid 2.0 Brightness Temperature (CETB) data at 37 GHz H-polarization with a high spatial resolution of 3.125 km. The CETB data were obtained from various satellite sensors with coarse spatial resolutions (~25 km), including SMMR on Nimbus 7, SSM/I and SSMIS on the DMSP satellite series, and AMSR-E on Aqua. Although the CETB data boast a higher spatial resolution than the original coarse-resolution pixels do, they are still derived from coarse-resolution data via the radiometer version of the scatterometer image reconstruction (rSIR) algorithm. This enhancement results in T_b data with resolutions ranging from 3.125 km to 12.5 km. Therefore, even with enhanced resolution, the pixels remain mixed to some extent due to the averaging and enhancement process (Section 3.1.1).

24. Line 199: How does including rules like “above 0 degrees” and “below 0 degrees” make mixed pixel classification better? I think I understand your logic, but I would like it spelled out in the manuscript

Reply: The decision to utilize specific temperature thresholds of "above 0 degrees" and "below 0 degrees" in our analysis is crucial for enhancing the accuracy of mixed pixel classification, particularly in the complex environment of Lake Ulansu. These thresholds are based on the fundamental physical properties of water and ice, where 0 °C marks the freezing point under atmospheric pressure, serving as a natural demarcation between the liquid and solid-states. This becomes particularly important in the context of Lake Ulansu, where mixed pixels often exhibit numerous abrupt change points (ACPs) in the brightness temperature (T_b) time series.

By implementing a rule that transitions from water to ice are recognized only at air temperatures below freezing point, we effectively reduce misclassification that might otherwise occur from transient T_b fluctuations or the influence of nonwater elements within the pixel, such as vegetation. Conversely, the rule that transitions from ice to water only occurs at air temperatures above freezing point helps accurately identify melting events, which is crucial for avoiding false interpretations of thawing during cold conditions. These air temperature-based rules simplify the classification process, providing clear and objective criteria that enhance our DMTT algorithm's ability to accurately calculate ice phenology in mixed pixels.

Revised text in the manuscript "*In addition to adhering to the ACP criteria outlined by Du et al. (2017), we tailor the DMTT algorithm to detect ACPs by accounting for seasonal variations and specific thermal conditions. We conducted separate ACP detection for T_b from August to December and from January to July. To ensure the accuracy of the ACP in indicating freezing transitions, ACPs detected from August to December were validated only if they were accompanied by air temperatures below the freezing point. Similarly, for ACPs from January to July, a prerequisite condition of air temperatures above the freezing point was applied to confirm melting transitions. The purpose of these two enhancements was to accommodate the variations in mixed pixels during the transitions between water and ice.*"

25. Line 201: what does the bar symbol above T_{b1} mean? What does b1 mean and b2 mean?

Reply: In the process outlined, $\overline{T_{b1}}$ and $\overline{T_{b2}}$ represent the mean brightness temperature (T_b) calculated 20 days before and after each detected abrupt change point (ACP), respectively. These averages are crucial for accurately determining the transitions between different states of water and ice.

The notation $\overline{T_{b1}}$ specifically indicates the mean T_b calculated from the time series data before the ACP, providing a baseline against which changes due to freezing can be detected. Conversely, $\overline{T_{b2}}$ represents the mean T_b after the ACP, which helps in identifying thawing events. By averaging the T_b values around each ACP, we minimize the influence of short-term fluctuations in T_b .

The terms b1 and b2 mentioned in the algorithm pertain to the calculated thresholds for freezing and melting, respectively. The freezing threshold is derived as the mean of the minimum $\overline{T_{b1}}$ and its corresponding $\overline{T_{b2}}$ within the same group of ACPs, indicating the transition from water to ice. The melting threshold, on the other hand, is calculated as the mean of the minimum $\overline{T_{b2}}$ and its associated $\overline{T_{b1}}$, facilitating the accurate detection of ice-to-water transitions.

26. Line 202: If means the average over 20 days, then how can there be a minimum?

Reply: The term "minimum" in our analysis refers not to the minimum of the brightness temperature (T_b) within those 20 days but to the selection of the lowest $\overline{T_{b1}}$ and $\overline{T_{b2}}$ values from different groups of ACPs for further calculations. Essentially, after computing the averages for each 20-day period surrounding each ACP, we then examine these average values across multiple ACPs to identify the lowest averages: where $\overline{T_{b1}}$ for freezing transitions and $\overline{T_{b2}}$ for thawing transitions.

This approach allows us to determine the most representative thresholds for freezing and melting by selecting the most stable and consistent average values, which reflect the most significant changes in the ice/water state. By using the minimum of these averages, we ensure that our thresholds for ice formation and melting are based on the most pronounced and reliable data points, thereby enhancing the accuracy of the DMTT algorithm in determining ice phenology.

27. Line 214: Were the multisource Sentinel, Landsat, and MODIS?

Reply: Thank you for highlighting the need for clarity regarding the multisource optical satellite data used to validate the DMTT algorithm.

Revised text in manuscript "*The results of the DMTT algorithm were validated through a comparison with ice phenology data obtained from multisource optical satellite data from 2000 to 2023 (Section 3.1.2).*"

28. Lines 215 -220: I think some of this text belongs in the results section to test the validity of the DMTT model

Reply: We have relocated the relevant text, which previously detailed the validation of the DMTT algorithm, from its initial location to the results section (Section 4.1).

29. Line 235: which phenology datasets did you use? Which meteorological datasets did you use?

Reply: The text in the manuscript "*To train and validate the RF model, we randomly divided the dataset, which includes ERA5 meteorological factors and ice phenology derived from T_b data for the period 1979 to 2023, into two subsets.*"

30. Line 255: Did you validate or ground truth your model using in-situ data?

Reply: In our study, we employed a robust validation approach. To ensure comprehensive coverage and unbiased validation across more than four decades, we randomly divided this dataset into two subsets: 70% was used for training the model, and 30% was used for validation. This random stratification

prevents any temporal biases that might arise from the use of distinct periods for training and validation (e.g., 1979–1990 for validation and 1991–2023 for training). Furthermore, for additional validation of the meteorological data, refer to Appendix A, where the performance of the ERA5 data is assessed. The ice phenology estimates derived from the brightness temperature calculations were cross-validated against corresponding results obtained from optical satellite data (Section 4.1).

31. Figure 6: How did you choose 1982 as the threshold change? I would include significance values in the figure directly. For example, only drawing lines and indicating trends if the results are significant

Reply: We chose 1982 as the threshold change based on the analysis of the 21-year moving averages (10 years before and after) of the freeze-up start (FUS), break-up end (BUE), and ice cover duration (ICD) periods. As shown in Fig. R3 (included in Appendix D), after 1982, there was a noticeable trend where FUS was delayed and the ICD was shortened. This marked change in trends approximately 1982 led us to select it as the threshold point.

To provide a more detailed depiction of this reversal, we divided the whole period into two subperiods (1941–1982 and 1983–2023) for further analysis. The corresponding statistical results are presented in Table 2 of the manuscript. Additionally, we have now included significance values (p values) directly in Figure 6 to indicate the statistical significance of the trends.

Revised text in the manuscript "*The results of the DMTT algorithm were validated through a comparison with ice phenology data obtained from multisource optical satellite data from 2000 to 2023 (Section 3.1.2). Figure 4 reveals a remarkably high correlation for the FUS dates ($r = 0.92$), with a minimal MAE of 2.00 days and an RMSE of 2.56 days. The correlation for the BUE date is slightly lower ($r = 0.87$), with a somewhat greater MAE of 2.67 days and an RMSE of 3.25 days. However, the MAEs and RMSEs for the ICDs calculated based on the difference between the BUE and FUS dates remain within 5 days, indicating no systematic bias but random errors.*"

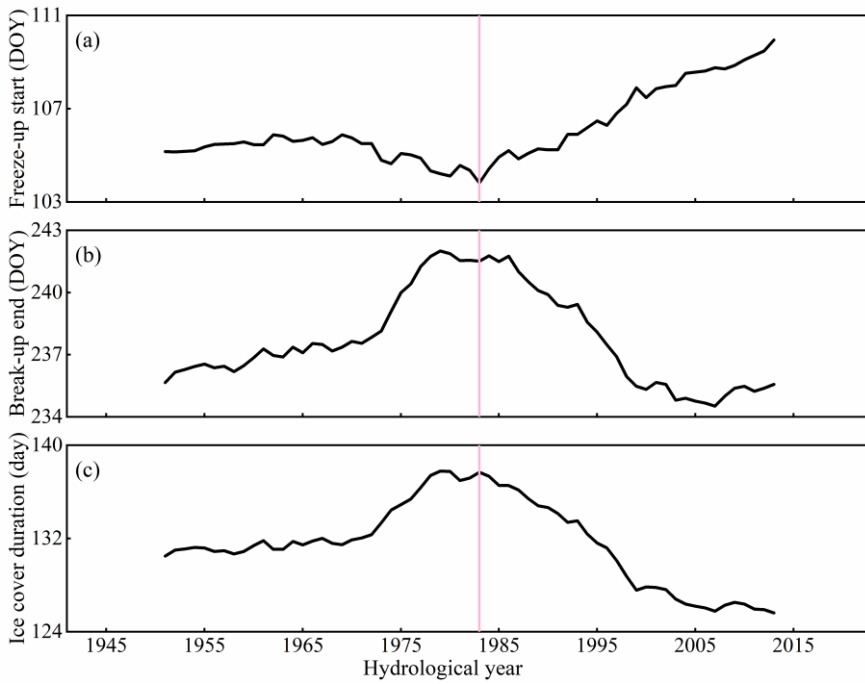


Figure R3: 21-year moving averages of ice phenology for Lake Ulusu. (a): Freeze-up start dates. (b): Break-up end dates. (c): Ice cover duration. The pink vertical line indicates the year 1983.

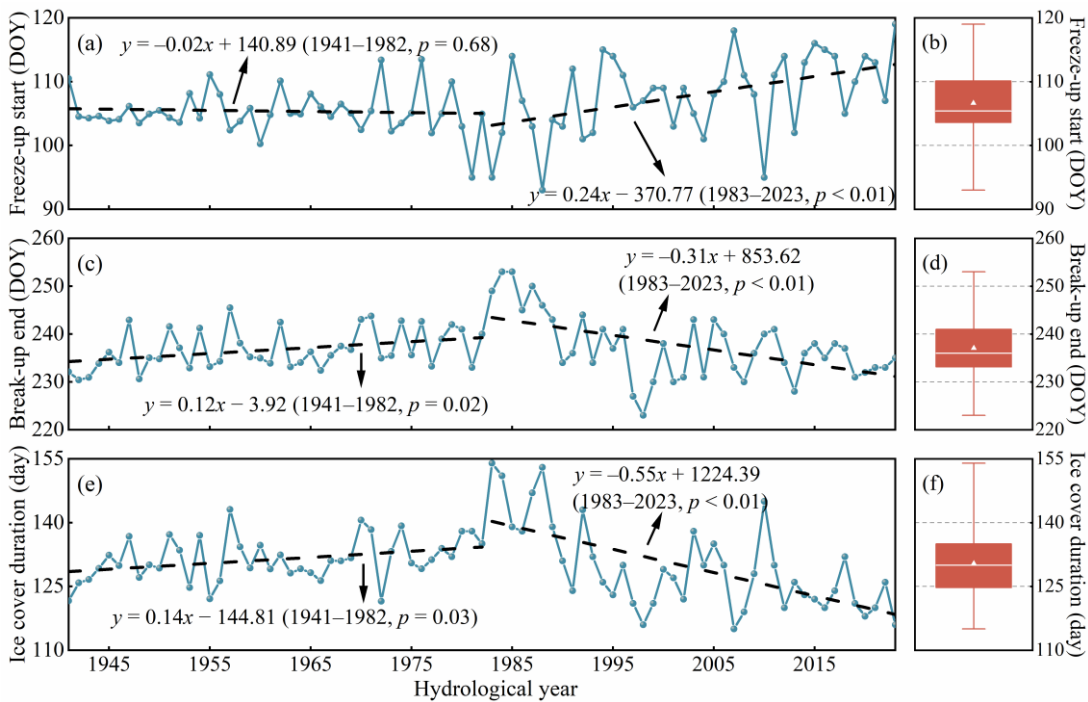


Figure 6: Ice phenology results for Lake Ulusu from 1941 to 2023. (a) Freeze-up start with trend lines. (b) Freeze-up start date distribution. (c) Break-up end with trend lines. (d) Break-up end date distribution. (e) Ice cover duration with trend lines. (f) Ice cover duration distribution.

32. Line 284: Do you have a citation for the statement “ice phenology is primarily determined by local meteorological conditions”?

Reply: We have added citations to support the statement that ice phenology is primarily determined by local meteorological conditions. See details on lines 291-292.

33. Line 292: This comment about Lake Mendota feels more like a methods comment

Reply: The text in the manuscript "*The observed air temperature fluctuations echo broader climate changes and show similar trends to those observed in other lakes (Magee et al., 2016; Newton and Mullan., 2021).*"

34. Figure 7: I would recommend moving this to the supplementary text, I feel that the preceding text does a good job summarizing the information.

Reply: Revised accordingly.

35. Line 331: Is there evidence that the preceding 12 months weather data could impact ice formation? I am not sure that each monthly correlation is necessary.

Reply: Thank you for your insightful question. We re-evaluated the monthly correlations and decided to focus on the months from September to March, which are more directly relevant to ice phenology and correspond to the months used in our random forest model calculations for ice phenology. We also modified the range of results in Figure 7.

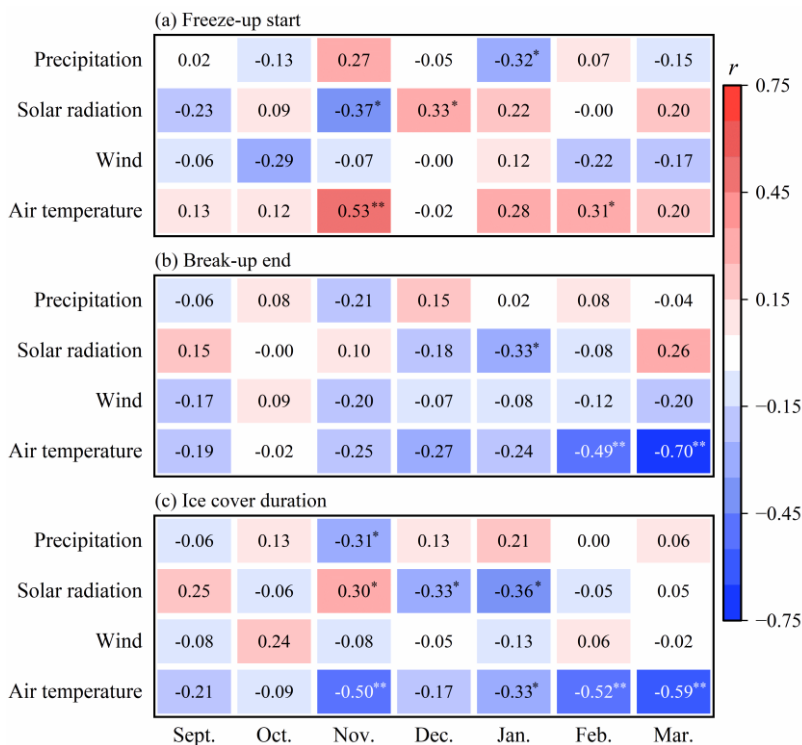


Figure 7: Correlation coefficients between meteorological factors and ice phenology in different months. Significance

levels for correlation coefficients are denoted by * ($p < 0.05$) and ** ($p < 0.01$).

36. Line 330: I am not sure that I followed the logic regarding solar radiation and algae and attenuation. I was wondering if the authors would consider expanding on this mechanism

Reply: In eutrophic lakes, due to the high concentrations of algae and suspended particles, the absorption and penetration of solar radiation differ significantly from those in clear lakes. Eutrophic lakes are rich in nutrients (such as nitrogen and phosphorus), promoting the proliferation of algae and phytoplankton (Li et al., 2024). These algae and suspended particles absorb and scatter solar radiation, especially blue light (450–495 nm). After being absorbed, this light energy is converted into heat or used for photosynthesis (Lin et al., 2024).

Because blue light is strongly absorbed, the penetration depth of light in water is significantly reduced. In clear lakes, light can penetrate deeper into the water column, but in eutrophic lakes, light is mainly absorbed and scattered by algae and suspended particles near the surface, reducing the penetration depth of light. Consequently, the heating effect of solar radiation on water is diminished.

The revised text in the manuscript "*For Lake Ulansu, the correlation may be due to the high attenuation coefficient caused by the presence of numerous suspended particles and algae, which are common in eutrophic lakes (Yang et al., 2020). These particles and algae absorb and scatter solar radiation, especially blue light (450–495 nm), reducing the penetration depth of light in water (Lin et al., 2024). As a result, the heating effect of solar radiation is confined primarily to the surface layers, leading to a diminished overall heating effect on the water.*"

37. Figure 8: Are you correlating FUS and BUE and ICD with months that occur after ice cover? It seems that in BUE and ICD the months stop at March, which feels appropriate. But, for freeze-up start, the months from Dec to Mar occur after the event and cannot correlate with the event as they cannot influence the event anymore.

Reply: We have revised Figure 7 to focus on the relevant months for each ice phenology event. We appreciate your attention to this detail, which enhances the accuracy and relevance of our analysis.

38. Section 5, Discussion: I would recommend starting this section with an overarching paragraph of main findings before delving into each subsection

Reply: We added this overarching paragraph to the Discussion, which reads "*The novel DMTT algorithm developed in this study has proven essential for accurately discerning ice and water states in a lake with*

mixed pixel challenges. In this section, we discuss the uncertainties associated with methodologies, compare our findings with those of other studies, and elaborate on the implications of the results for understanding the impacts of climate change on lake ice phenology."

39. Line 274: If the pixels chosen in the CETB database are such that they reduce the effects of mixed pixels, how do you know if your DMTT algorithm does a better job at overcoming mixed pixels.

Reply: The effectiveness of the DMTT algorithm in managing the challenges posed by mixed pixels in Lake Ulansu, even with the selection of higher resolution CETB data at 3.125 km. While these selected pixels indeed have greater water coverage, reducing the influence of nonwater elements, they do not entirely eliminate the complexities associated with mixed pixel conditions. Compared with the MTT algorithm, the DMTT algorithm offers significant improvements in addressing these complexities (Section 4.1). By employing a double-threshold approach, the DMTT algorithm specifically adapts to the nuanced variations between ice and water states observed in Lake Ulansu. This method allows for a more accurate identification of state changes in mixed pixels, reducing the likelihood of undetected transitions, which are more common with simpler, single-threshold approaches. Furthermore, our comparative analysis between the DMTT and MTT algorithms demonstrates that the DMTT provides a better fit for the specific conditions of Lake Ulansu (Section 4.1). It more effectively reduces the incidence of undetected states, enhancing the dataset's overall accuracy. This is supported by the robust validation against multisource optical satellite data, which corroborates the DMTT algorithm's performance in handling complex mixed pixel scenarios.

40. Line 298: I would elaborate on this further. If most lakes in the Northern Hemisphere that have data are deep lakes, but shallow lakes are abundant? Then what about the comparison between the two makes it interesting? (I agree with you that it would be interesting, but I would like to know your reasoning)

Reply: The comparison between shallow and deep lakes is indeed intriguing and scientifically valuable for several reasons:

- (1) Methodological insights: Comparing different lake types can also refine our methodological approaches in limnology and cryosphere sciences. It challenges existing algorithms and encourages the development of new techniques suitable for diverse conditions, as demonstrated by our DMTT algorithm for Lake Ulansu.
- (2) Differential thermal dynamics: Shallow lakes, such as Lake Ulansu, have minimal water volumes and shallow depths which lead to faster thermal responses. This characteristic makes them highly sensitive

to atmospheric temperature changes, allowing them to serve as early indicators of climate change effects. In contrast, deeper lakes with larger volumes exhibit greater thermal inertia, delaying their response to climatic shifts. By comparing these systems, we can better understand the spectrum of lake responses to global warming, providing a broader perspective on thermal dynamics under changing climatic conditions.

(3) Ice cover variability: The dynamics of ice cover in shallow lakes are markedly different from those in deeper lakes because of their rapid thermal response and shallower thermocline. Shallow lakes tend to freeze and thaw more quickly, which could lead to a shorter ice cover duration (ICD) under warming scenarios. In deeper lakes, the ICD is generally longer because of its their ability to retain cold temperatures. Studying these differences helps illuminate how variations in lake depth influence ice phenology, which is crucial for predicting ecological impacts across different lake types.

These points have been elaborated upon in the revised manuscript to better articulate the scientific significance of comparing shallow and deep lakes, thereby clarifying the unique contributions of our study to the fields of limnology and climate science. See details on lines 404-442.

41. Line 402: Can you qualify why you chose to compare Lake Ulansu with Qinghai Lake?

Reply: This comparison is instrumental in highlighting the distinct phenological responses of lakes with different physical and ecological characteristics under similar climatic latitudes. Qinghai Lake, one of the largest saline lakes in a high-altitude environment and a widely studied subject, offers a robust dataset, including long-term ice phenology data. These high-quality, extensive datasets make Qinghai Lake an ideal reference point for assessing trends and methodologies, enhancing the validity of our comparative analysis.

The key differences in their physical attributes—such as depth and salinity—result in varied responses to climatic factors, particularly air temperature and solar radiation, which influence their freeze-up start and break-up end dates. By comparing these two lakes, we aim to illustrate how varying lake characteristics can affect ice phenology, thus providing broader insights into how different types of lakes might respond to climate change. Qinghai Lake, with its larger volume and more saline water, has different thermal inertia and sensitivity to temperature changes than does the more responsive Lake Ulansu. This comparative analysis not only enriches our understanding of lake response but also supports the development of more nuanced models for predicting lake ice dynamics across diverse ecological settings. See details on lines 407-420.

42. 5.2 Comparison with other lakes: In general, I think this section needs to be better qualified, why did you choose the comparisons with Qinghai Lake or the northern European lakes? What are some major consequences of the similarities/differences? How do you think adding shallow lakes will change our contextual understanding of lake ice, globally? Or locally?

Reply: We have restructured this section to provide a clearer rationale for our choice of comparative studies with Qinghai Lake and the lakes in Northern Europe. This revision includes a more detailed discussion on why these particular comparisons are pertinent and how they contribute to the broader understanding of lake ice phenology under varying climatic and geographic conditions.

43. 5.3 Conclusion: This section is extremely well written and summarizes the study well

Reply: Thank you for your encouraging feedback on the Conclusion section of the manuscript.

44. Line 455: Is there a citation associated with this, or is this in comparison to the other lakes in section 5.3?

Reply: We have revised the statement to emphasize the pronounced reduction in ice cover duration (ICD) observed at Lake Ulansu over the last four decades. We note that this change is significantly more marked than the gradual trends in the ICD across other Northern Hemisphere lakes. See details on lines 455-459.

45. Line 54 add CERP acronym here

Reply: Revised accordingly.

References:

Antonova, S., Duguay, C., Kääh, A., Heim, B., Langer, M., Westermann, S., and Boike, J.: Monitoring Bedfast Ice and Ice Phenology in Lakes of the Lena River Delta Using TerraSAR-X Backscatter and Coherence Time Series, *Remote Sens.*, 8, doi:10.3390/rs8110903, 2016.

Ambrosetti, W. and Barbanti, L.: Deep water warming in lakes: an indicator of climatic change, *J. Limnol.*, 58, doi:10.4081/jlimnol.1999.1, 1999.

Bartosiewicz, M., Ptak, M., Woolway, R. I., and Sojka, M.: On thinning ice: Effects of atmospheric warming, changes in wind speed and rainfall on ice conditions in temperate lakes (Northern Poland), *J. Hydrol.*, 597, doi:10.1016/j.jhydrol.2020.125724, 2021.

Brodzik, M., Long, D., Hardman, M., Paget, A., and Armstrong, R.: MEASURES calibrated enhanced-resolution passive microwave daily EASE-grid 2.0 brightness temperature ESDR, version 1, Digital Media, doi:10.5067/MEASURES/CRYOSPHERE/NSIDC-0630.001, 2016.

Cai, Y., Duguay, C. R., and Ke, C.-Q.: A 41-year (1979–2019) passive-microwave-derived lake ice phenology data record of the Northern

Hemisphere, *Earth Syst. Sci. Data*, 14, 3329–3347, doi:10.5194/essd-14-3329-2022, 2022.

Cai, Y., Ke, C. Q., Li, X., Zhang, G., Duan, Z., and Lee, H.: Variations of Lake Ice Phenology on the Tibetan Plateau From 2001 to 2017 Based on MODIS Data, *J. Geophys. Res. Atmos.*, 124, 825–843. doi:10.1029/2018JD028993, 2019.

Duan, H., Ma, R., and Hu, C.: Evaluation of remote sensing algorithms for cyanobacterial pigment retrievals during spring bloom formation in several lakes of East China, *Remote Sens. Environ.*, 126, 126–135, doi:10.1016/j.rse.2012.08.011, 2012.

Giroux-Bougard, X., Fluet-Chouinard, E., Crowley, M. A., Cardille, J. A., and Humphries, M. M.: Multi-sensor detection of spring breakup phenology of Canada's lakes, *Remote Sens. Environ.*, 295, doi:10.1016/j.rse.2023.113656, 2023.

Heinilä, K., Mattila, O.-P., Metsämäki, S., Väkevä, S., Luojus, K., Schwaizer, G., and Koponen, S.: A novel method for detecting lake ice cover using optical satellite data, *Int. J. Appl. Earth Obs. Geoinf.*, 104, doi:10.1016/j.jag.2021.102566, 2021.

Howell, S. E. L., Brown, L. C., Kang, K.-K., and Duguay, C. R.: Variability in ice phenology on Great Bear Lake and Great Slave Lake, Northwest Territories, Canada, from SeaWinds/QuikSCAT: 2000–2006, *Remote Sens. Environ.*, 113, 816–834, doi:10.1016/j.rse.2008.12.007, 2009.

Huo, P., Lu, P., Cheng, B., Zhang, L., Wang, Q., and Li, Z.: Monitoring Ice Phenology in Lake Wetlands Based on Optical Satellite Data: A Case Study of Wuliangsu Lake, *Water*, 14, doi:10.3390/w14203307, 2022.

Kirillin, G., Leppäranta, M., Terzhevik, A., Granin, N., Bernhardt, J., Engelhardt, C., Efremova, T., Golosov, S., Palshin, N., Sherstyankin, P., Zdorovenova, G., and Zdorovenov, R.: Physics of seasonally ice-covered lakes: a review, *Aquat. Sci.*, 74, 659–682, doi:10.1007/s00027-012-0279-y, 2012.

Korver, M. C., Lehner, B., Cardille, J. A., and Carrea, L.: Surface water temperature observations and ice phenology estimations for 1.4 million lakes globally, *Remote Sens. Environ.*, 308, doi:10.1016/j.rse.2024.114164, 2024.

Kuluwan, Y., Rusuli, Y., and Ainiwaer, M.: Monitoring of Lake Ice Phenology Changes in Bosten Lake Based on Bayesian Change Detection Algorithm and Passive Microwave Remote Sensing (PMRS) Data, *Sensors*, 23, doi:10.3390/s23249852, 2023.

Latifovic, R. and Pouliot, D.: Analysis of climate change impacts on lake ice phenology in Canada using the historical satellite data record, *Remote Sens. Environ.*, 106, 492–507, doi:10.1016/j.rse.2006.09.015, 2007.

L'Abée-Lund, J. H., Vøllestad, L. A., Brittain, J. E., Kvambekk, Å. S., and Solvang, T.: Geographic variation and temporal trends in ice phenology in Norwegian lakes during the period 1890–2020, *Cryosphere*, 15, 2333–2356, doi:10.5194/tc-15-2333-2021, 2021.

Leppäranta, M.: Freezing of lakes and the evolution of their ice cover, Springer-Praxis, Heidelberg, Germany, 2023.

Li, H., Song, C., Yang, L., Qin, H., Cao, X., and Zhou, Y.: Phosphorus supply pathways and mechanisms in shallow lakes with different regime, *Water Resour.*, 193, 116886, doi:10.1016/j.watres.2021.116886, 2021.

Li, L., and Xue, B.: Methane emissions from northern lakes under climate change: a review, *SN Appl. Sci.*, 3, 883, doi:10.1007/s42452-021-04869-x, 2021.

Lin, X., Wu, X., Chao, J., Ge, X., Tan, L., Liu, W., Sun, Z., and Hou, J.: Effects of combined ecological restoration measures on water quality and underwater light environment of Qingshan Lake, an urban eutrophic lake in China, *Ecological Indicators*, 163,

doi:10.1016/j.ecolind.2024.112107, 2024.

Mishra, V., Cherkauer, K. A., Bowling, L. C., and Huber, M.: Lake Ice phenology of small lakes: Impacts of climate variability in the Great Lakes region, *Glob. Planet. Change*, 76, 166–185, doi:10.1016/j.gloplacha.2011.01.004, 2011.

Munn, R. E., and Richards, T.L.: Vertical temperature profiles over adjacent land and lake stations, *Q. J. R. Meteorol. Soc.*, 89, 411–413, doi:10.1002/qj.49708938113, 1963.

Woolway, R. I., Kraemer, B. M., Lenters, J. D., Merchant, C. J., O'Reilly, C. M., and Sharma, S.: Global lake responses to climate change, *Nat. Rev. Earth Environ.*, 1, 388–403, doi:10.1038/s43017-020-0067-5, 2020.

Ruan, Y., Zhang, X., Xin, Q., Qiu, Y., and Sun, Y.: Prediction and Analysis of Lake Ice Phenology Dynamics Under Future Climate Scenarios Across the Inner Tibetan Plateau, *J. Geophys. Res.-Atmos.*, 125, doi:10.1029/2020jd033082, 2020.

Sharma, S., Blagrove, K., Magnuson, J. J., O'Reilly, C. M., Oliver, S., Batt, R. D., Magee, M. R., Straile, D., Weyhenmeyer, G. A., Winslow, L., and Woolway, R. I.: Widespread loss of lake ice around the Northern Hemisphere in a warming world, *Nat. Clim. Chang.*, 9, 227–231. doi:10.1038/s41558-018-0393-5, 2019.

Sharma, S., Richardson, D. C., Woolway, R. I., Imrit, M. A., Bouffard, D., Blagrove, K., Daly, J., Filazzola, A., Granin, N., Korhonen, J., Magnuson, J., Marszelewski, W., Matsuzaki, S. I. S., Perry, W., Robertson, D. M., Rudstam, L. G., Weyhenmeyer, G. A., and Yao, H.: Loss of Ice Cover, Shifting Phenology, and More Extreme Events in Northern Hemisphere Lakes, *J. Geophys. Res.-Biogeosci.*, 126, doi:10.1029/2021jg006348, 2021.

Smits, A. P., Gomez, N. W., Dozier, J., and Sadro, S.: Winter Climate and Lake Morphology Control Ice Phenology and Under-Ice Temperature and Oxygen Regimes in Mountain Lakes, *J. Geophys. Res.-Biogeosci.*, 126, doi:10.1029/2021jg006277, 2021.

Su, L., Che, T., and Dai, L.: Variation in Ice Phenology of Large Lakes over the Northern Hemisphere Based on Passive Microwave Remote Sensing Data, *Remote Sens.*, 13, doi:10.3390/rs13071389, 2021.

Sun, B., Li, C. Y., and Zhu, D. N.: Changes of Ulansuhai Lake in past 150 years based on 3S technology, 2011 International Conference on Remote Sensing, Environment and Transportation Engineering, 2993–2997, doi:10.1109/rsete.2011.5964944, 2011.

Wilheit, T., Nordberg, W., Blinn, J., Campbell, W., and Edgerton, A.: Aircraft measurements of microwave emission from arctic sea ice, *Remote Sens. Environ.*, 2, 129–139, doi:10.1016/0034-4257(71)90087-3, 1972.

White, I., Xu, T., Zeng, J., Yu, J., Ma, X., Yang, J., Huo, Z., and Chen, H.: Changing climate and implications for water use in the Hetao Basin, Yellow River, China, *Proc. IAHS*, 383, 51–59, doi:10.5194/piahs-383-51-2020, 2020.

Wu, Y., Duguay, C. R., and Xu, L.: Assessment of machine learning classifiers for global lake ice cover mapping from MODIS TOA reflectance data, *Remote Sens. Environ.*, 253, doi:10.1016/j.rse.2020.112206, 2021.

Wu, Y., Guo, L., Zhang, B., Zheng, H., Fan, L., Chi, H., Li, J., and Wang, S.: Ice phenology dataset reconstructed from remote sensing and modelling for lakes over the Tibetan Plateau, *Sci. Data*, 9, doi:10.1038/s41597-022-01863-9, 2022.

Xu, Y., Long, D., Li, X., Wang, Y., Zhao, F., and Cui, Y.: Unveiling lake ice phenology in Central Asia under climate change with MODIS data and a two-step classification approach, *Remote Sens. Environ.*, 301, doi:10.1016/j.rse.2023.113955, 2024.

Zhao, G., Li, Y., Zhou, L., and Gao, H. L.: Evaporative water loss of 1.42 million global lakes, *Nat. Commun.*, 13, 3686, doi:10.1038/s41467-

022-31125-6, 2022.

Yang, W., Xu, M., Li, R., Zhang, L., and Deng, Q.: Estimating the ecological water levels of shallow lakes: a case study in Tangxun Lake, China, *Sci Rep*, 10, doi:10.1038/s41598-020-62454-5, 2020.

Zhang, S. and Pavelsky, T. M.: Remote Sensing of Lake Ice Phenology across a Range of Lakes Sizes, ME, USA, *Remote Sens.*, 11, doi:10.3390/rs11141718, 2019.