

ESA Climate Space Tipping Elements Project

RESET lakes

Science Requirements

Version 1.1

21 November 2025

Authors

Elisa Calamita

Iestyn Woolway

Caren Binding

Michael Brechbühler

Daniel Odermatt

Content

1	Introduction	2
2	Thermal stratification of lakes	6
2.1	<i>Vertical mixing regime shifts</i>	6
2.2	<i>Thermal bar detection in LSWT products</i>	6
2.3	<i>Knowledge gaps</i>	7
2.4	<i>Further research on remote sensing of thermal bars in lakes</i>	8
3	Lake ice cover	10
3.1	<i>Shifts in lake ice phenology</i>	10
3.2	<i>Global lake ice variations and the impact of air temperature</i>	11
3.3	<i>Knowledge gaps</i>	11
3.4	<i>Regional scale lake ice monitoring</i>	12
4	Lake browning	13
4.1	<i>Drivers and impacts of lake brownification</i>	13
4.2	<i>Status of lake browning and potential tipping points</i>	14
4.3	<i>Satellite Remote Sensing of Lake DOC</i>	15
5	Plankton phenology	17
5.1	<i>What is tipping?</i>	17
5.2	<i>Preliminary work</i>	17
5.3	<i>Knowledge gaps</i>	18
5.4	<i>Potential contribution from EO</i>	18
6	Combined lake processes	18
6.1	<i>Links between ice, stratification and phytoplankton phenology</i>	18
6.2	<i>Preliminary work</i>	20
6.3	<i>Knowledge gaps</i>	21
6.4	<i>Potential contribution from EO</i>	22
7	Surface water albedo	23
7.1	<i>The variability of lake surface albedo</i>	23
7.2	<i>Representation of water surface albedo in weather and climate models</i>	25
7.3	<i>Knowledge gaps</i>	27
7.4	<i>Potential contribution from EO</i>	27
8	References	28

1 Introduction

Lakes are undergoing rapid transformations in response to climate change (Woolway et al. 2020b; Zhang et al. 2023). These changes can unfold gradually over time, but they may also occur abruptly and without warning. In some cases, they can trigger sudden shifts in ecosystem states when critical tipping points are crossed (Scheffer et al. 2001b, 2009a; Milkoreit et al. 2018a; Mesman et al. 2021). Surpassing these thresholds, referred to as lake shifts, can lead to profound and rapid changes in lake processes, resulting in cascading ecological and environmental impacts such as disrupted trophic interactions and restructured food webs (Wagner and Adrian 2009a; Hébert et al. 2021a).

Out of 449 reviewed studies on climate-related shifts in lakes (Calamita et al. 2024), only about 9% utilized satellite Earth Observation (EO) data. However, the use of EO has increased significantly since 2012. EO has primarily been applied to detect physical shifts in lakes, such as changes in surface area or ice cover. These variables are well-suited to EO because they can be directly observed with high spatial and temporal resolution from satellite imagery. In addition, select biogeochemical variables such as chlorophyll-a have allowed detection of, for example, shifts in phytoplankton phenology in lakes. In contrast, EO has proven less effective for detecting chemical shifts, which often require indirect inference. For instance, while surface reflectance patterns can help infer processes like vertical mixing or suspended particulate matter concentrations, key variables such as dissolved oxygen or nutrient levels remain challenging to measure using EO alone.

The relatively low incorporation of EO in lake shift studies reflects several challenges, including limitations in sensor accuracy, time series length and associated multi-mission data continuity, calibration needs, and overall data accessibility. Despite these constraints, the review highlights the strong potential of EO technologies to enhance early-warning systems and improve long-term monitoring of lakes undergoing climate-related changes. EO's main advantage lies in its ability to provide consistent, large-scale observations over time, making it valuable for detecting trends and identifying abrupt transitions, potentially even before they become apparent through conventional monitoring. As satellite capabilities continue to improve, the authors suggest EO will play an increasingly vital role in capturing lake shifts at regional to global scales and in near-real-time.

Since the completion of the previous systematic review up to 2021, an updated search was conducted on July 7, 2025, using the same Web of Science query focused on tipping points, regime shifts, and related phenomena in lakes and inland waters under climate change or warming conditions. This search yielded 360 additional records (Figure 1). Although an in-depth screening has not been performed on the total pool of papers as for the published review in Calamita et al. (2024), the results highlight a continued research interest in the effects of climate change on freshwater ecosystem shifts. The total of 360 records retrieved in this updated search includes our review article published in 2024 and titled "Detecting climate-related shifts in lakes: a review of the use of satellite Earth Observation", validating the potential of capturing new publications on this topic.

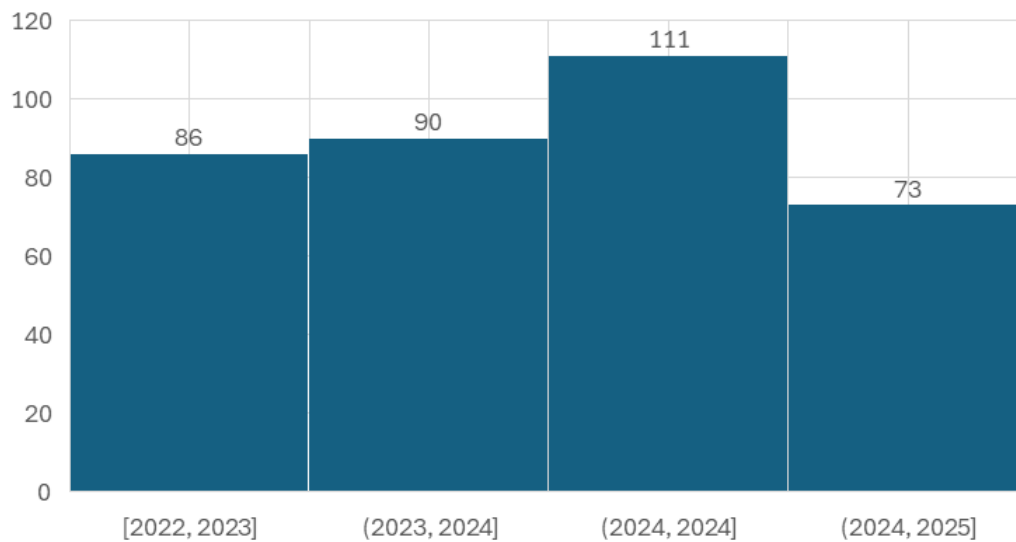


Figure 1: Scientific articles on climate-driven lake shifts published after the period reviewed in the literature review of Calamita et al. 2024.

Out of the 360 papers retrieved from our Web of Science search, we screened for articles where the use of EO could be further leveraged to address the study objectives. Through this careful selection process, we identified approximately 30 key papers that we found particularly relevant and inspiring for highlighting knowledge gaps and identifying priority research areas. A list of these papers is summarized in Table 1. The selected studies collectively address shifts in physical, chemical, and biological lake processes.

Table 1: Selected 2022-2025 lake regime shift publications.

#	Title	Journal	Year
1	What interrupted monomictic mixing in Lake Biwa? Heat budget analysis using a circulation model	Hydrol. Sci. J.	2023
2	Regime Shifts in Lake Oxygen and Temperature in the Rapidly Warming High Arctic	Geophys. Res. Lett.	2024
3	Lake ecosystem tipping points and climate feedbacks	Earth Syst. Dynam.	2024
4	Changes in the stratification and mixing patterns of Lake Bosumtwi due to climate warming	Fundam. Appl. Limnol.	2025
5	Regime shifts, trends, and variability of lake productivity at a global scale	Proc. Natl. Acad. Sci. U. S. A.	2022
6	Evidence of summer thermal stratification in extreme northern lakes	Arct. Sci.	2024
7	Abrupt ecological shifts of lakes during the Anthropocene	Earth-Sci. Rev.	2022
8	Global warming triggers abrupt regime shifts in island lake ecosystems in the Azores Archipelago	Commun. Earth Environ.	2024
9	Trends of lake temperature, mixing depth and ice cover thickness of European lakes during the last four decades	Sci. Total Environ.	2022
10	Reduced precipitation can induce ecosystem regime shifts in lakes by increasing internal nutrient recycling	Sci Rep	2024
11	Phenological Shifts in Lake Ice Cover Across the Northern Hemisphere: A Glimpse Into the Past, Present, and the Future of Lake Ice Phenology	Water Resour. Res.	2024
12	Asynchronous multitrophic level regime shifts show resilience to lake browning	Sci. Total Environ.	2024

#	Title	Journal	Year
13	Regime shifts in satellite-derived chlorophyll within the Laurentian Great Lakes	J. Gt. Lakes Res.	2025
14	Classifying Mixing Regimes in Ponds and Shallow Lakes	Water Resour. Res.	2022
15	Numerical study on regime shifts in an urban subtropical shallow lake: Xinglong Lake, China	Ecol. Indic.	2023
16	Arctic warming drives striking twenty-first century ecosystem shifts in Great Slave Lake (Subarctic Canada), North America's deepest lake	Proc. R. Soc. B-Biol. Sci.	2023
17	Abrupt changes in algal biomass of thousands of US lakes are related to climate and are more likely in low- disturbance watersheds	Proc. Natl. Acad. Sci. U. S. A.	2025
18	Climate change-induced amplification of extreme temperatures in large lakes	Commun. Earth Environ.	2025
19	Abrupt transformation of West Greenland lakes following compound climate extremes associated with atmospheric rivers	Proc. Natl. Acad. Sci. U. S. A.	2025
20	Nonlinear responses in interannual variability of lake ice to climate change	Limnol. Oceanogr.	2024
21	Regime shifts in shallow lakes explained by critical turbidity	Water Res.	2023
22	The interaction of physical structure and nutrient loading drives ecosystem change in a large tropical lake over 40 years	Sci. Total Environ.	2022
23	Investigating lake chlorophyll-a responses to the 2019 European double heatwave using satellite remote sensing	Ecol. Indic.	2022
24	Anthropogenic forcing leads to an abrupt shift to phytoplankton dominance in a shallow eutrophic lake	Freshw. Biol.	2024
25	Annual patterns of stratification, mixing and ventilation in long, deep, seasonally ice-covered Francois lake, British Columbia, Canada	Front. Earth Sci.	2023
26	Identifying the true drivers of abrupt changes in ecosystem state with a focus on time lags: Extreme precipitation can determine water quality in shallow lakes	Sci. Total Environ.	2023
27	Nonlinear dynamics of ecosystem productivity and its driving mechanisms in arid regions: A case study of Ebinur Lake Basin	J. Environ. Manage.	2025
28	Seasonal wet-dry transition and denitrifying communities contributed to nitrous oxide emissions in the water-level fluctuating zone of the largest freshwater lake in China	J. Hydrol.	2024
29	Teleconnection Between Early Winter Monsoon System and Harmful Algal Blooms in Shallow Lake Taihu	Water Resour. Res.	2024
30	Inferring causal impacts of extreme water-level drawdowns on lake water clarity using long-term monitoring data	Sci. Total Environ.	2022
31	Global seasonal dynamics of inland open water and ice	Remote Sens. Environ.	2022

Furthermore, recent reviews of ecosystem tipping points highlight several critical scientific needs that remain relevant for the study of lakes and freshwater systems. (Yi et al. 2025) provide a conceptual framework for advancing resilience and tipping-point science, emphasizing standardized definitions, rigorous detection of critical thresholds, and integration of interdisciplinary methods. Their framework advocates for modeling both deterministic and stochastic drivers, detecting early-warning signals, quantifying resilience metrics, and ranking tipping points by their potential consequences. Crucially, they stress that research should bridge spatial and temporal scales, connect ecosystem dynamics to broader climate feedbacks, and translate findings into actionable tools for governance, monitoring, and management.

Based on our literature review and recent publications, we have identified several key knowledge gaps in understanding and monitoring climate-driven tipping points in lakes. These gaps span physical, chemical, and biological processes, highlighting the complex and interconnected nature of lake systems, where shifts in thermal regimes, ice cover, biogeochemistry, and ecological responses are tightly coupled (Figure 2). EO technologies offer unique opportunities to address these gaps by providing spatially and temporally consistent measurements of lake essential climate variables (ECVs), such as surface temperature, ice cover, water extent, and optical properties (Pickens et al. 2022; Carrea et al. 2023; Calamita et al. 2024).

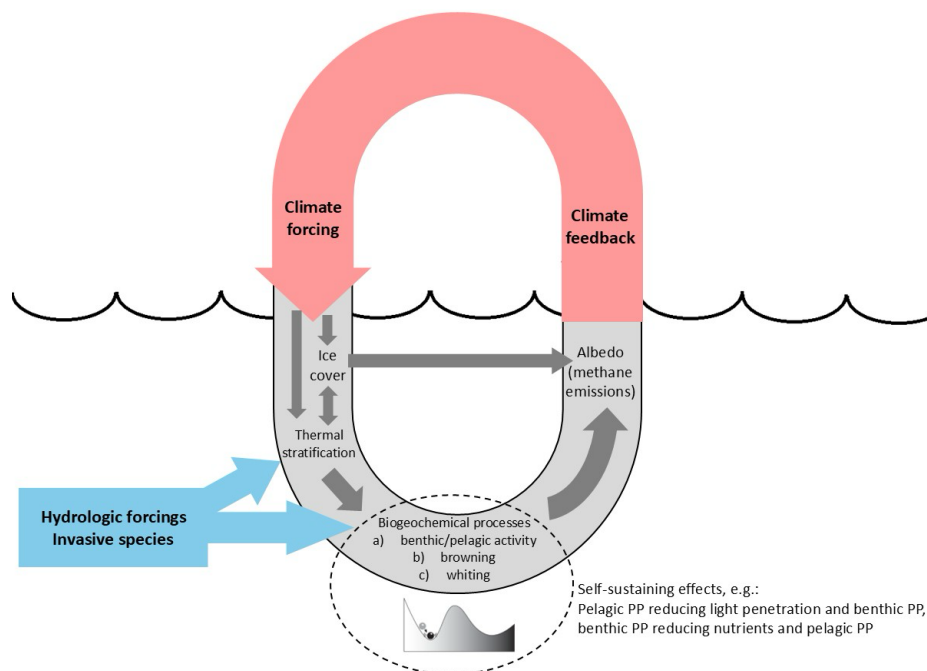


Figure 2: Coupling of climatological and hydrological drivers, limnological processes and feedback mechanisms. Tipping points are reached when lake variables shift towards new, self-sustaining equilibria.

The primary objective of RESETlakes is to identify tipping points, i.e. lake variables shift towards new, self-sustaining equilibria using EO. Sections 2 to 5 address such properties and processes, namely thermal stratification, ice cover, browning and phytoplankton phenology. Section 6 describes how these individual lake variables are linked seasonally, and how these links can cause self-sustaining effects, e.g., if a change in stratification affects algae growth and hence transparency in the surface layer that again affects the thermal regime.

The secondary of RESETlakes was to investigate lake-climate feedback loops using EO data. In Section 7, we describe this feedback in scientific and technical terms for the potential effect of changing lake albedo on regional climates. This topic was investigated because satellite EO can potentially be used for direct retrievals of lake surface albedos. Contrariwise, the potential to estimate greenhouse gas fluxes of lakes even indirectly is very limited. Therefore, this topic was not further investigated.

Each of these topics is described in more detail in the following sections, including an assessment of how the results could contribute to understanding feedbacks between lake tipping points and the broader climate system, as required by the IPCC Assessment reports (e.g. AR6). By systematically combining EO observations with modeling and targeted in situ data, RESETLakes aims to expand our capacity to anticipate, track, and understand tipping points across European and global lakes, providing actionable insights for conservation, management, and climate mitigation strategies.

2 Thermal stratification of lakes

2.1 Vertical mixing regime shifts

Lake mixing is a key process in lake ecosystems. Lake thermal stratification, resulting from temperature-dependent water density gradients (Imboden and Wüest 1995), determines the vertical layering of the lake water column. Stratification is determined by the evolving balance between turbulence and buoyancy, two forces that act to enhance or suppress mixing respectively (Boehrer and Schultze 2008). This governs the transport of oxygen, nutrients, and energy within lakes, ultimately influencing processes such as the metabolic rates of greenhouse gases as well as the abundance and productivity of lake organisms (Livingstone 2003; Winder and Schindler 2004; Woolway and Merchant 2019; Jansen et al. 2022).

Climate change can strongly affect lake mixing regimes, the yearly patterns of lake stratification (Lewis 1983), potentially leading to regime shifts (Shatwell et al. 2019; Woolway and Merchant 2019). The response of lake mixing regimes to climate change is complex and influenced by several factors that contribute to the lake heat budget (Vanderkelen et al. 2020; Schmid and Read 2022). According to tipping point science, the exceedance of critical thresholds may trigger changes in the mixing regime of lakes (Woolway and Merchant 2019; Brovkin et al. 2025; Loriani et al. 2025) leading to alterations in various lake processes, including oxygenation and nutrient cycling. These alterations can cascade into ecological and environmental consequences, such as disrupted trophic linkages and shifts in food web dynamics (Wagner and Adrian 2009b; Hébert et al. 2021b). Thus, changes in the mixing regimes of lakes can trigger abrupt transitions in the state of lake ecosystems (Scheffer et al. 2001a, 2009b; Milkoreit et al. 2018b; Mesman et al. 2021) with far-reaching consequences for human activities (Gilarranz et al. 2022) as well as substantial feedback to climate change (Hessen et al. 2024).

2.2 Thermal bar detection in LSWT products

Despite the importance of understanding lake mixing regime shifts, we lack systematic knowledge of their occurrence worldwide (Calamita et al. 2024). Investigating these shifts requires long-term observations, which are often challenging to collect on a global scale. However, recent modelling studies suggest that many lakes projected to experience mixing regime shifts in the future may already exhibit mixing anomalies relative to their dominant mixing classification (Woolway and Merchant 2019). Therefore, detecting contemporary mixing anomalies in lakes is a critical step toward identifying those more susceptible to future mixing regime shifts.

Lake Surface Water Temperature (LSWT) has been extensively used to study surface warming trends in large lakes, primarily due to the availability of satellite observations during ice-free periods. However, while LSWT has provided valuable insights, its spatially explicit nature offers an underutilized opportunity for further exploration. Medium resolution satellite EO enables consistent and systematic monitoring of LSWT across the largest lakes globally (Politi et al. 2016), and these spatial datasets allow for the detection of thermal features such as thermal fronts, a method well-established in oceanography (Belkin and O'Reilly 2009). Similar features occur in lakes (Ullman et al. 1998; Fichot et al. 2019; Toffolon et al. 2020; Calamita et al. 2021), yet remain underexplored in limnological studies.

In our previous study about dimictic lakes, currently under revision, we utilize spatial gradients in remotely sensed LSWT to investigate lake mixing regimes, mixing anomalies and lakes that are approaching a mixing regime shift. Our assessment includes a classification scheme based solely on EO data to determine the contemporary mixing class of 1973 out of the 2024 globally distributed lakes included in the European Space Agency (ESA) Climate Change Initiative (CCI) Lake data repository (Lakes CCI hereafter, <https://climate.esa.int/en/projects/lakes/>, last visited June 2024). Additionally, we analyse the occurrence of mixing anomalies in these dimictic lakes over the past 22 years, presenting the first global assessment of lake mixing anomalies. Furthermore, we employ satellite EO to calculate the susceptibility of lakes to undergo a mixing regime shift (Calamita et al. 2025).

2.3 Knowledge gaps

Based on (Lorani et al. 2025) EO can be used to track the different stages of a tipping element, from initial destabilization through to a full transition into a new state. A central question in lake–climate research is therefore whether EO can detect and monitor the stages of a lake mixing regime shift, specifically, whether it can distinguish between cold monomictic lakes in an early destabilization phase and those that have already tipped into a new dimictic regime.

To investigate this, we carried out a pilot analysis using the LakesCCI surface water temperature dataset to assess how many lakes may have undergone such shifts over the past 22 years. Our approach focused on detecting temporal changes in surface thermal dynamics that indicate alterations in stratification and mixing behavior. We applied a thermal front tracking method, originally developed for dimictic lakes within the MixCI framework (Calamita et al. 2025) and extended it to cold monomictic systems. This enabled us to test whether EO can capture summer mixing anomalies, which are expected to precede regime shifts in cold monomictic lakes.

Our preliminary results indicate that nine cold monomictic lakes out of ten exhibited at least one year of anomalous dimictic-like mixing behavior over the last two decades. These findings, summarized in Table 2, provide initial evidence that EO can capture early signs of mixing regime destabilization, offering a pathway to track and anticipate climate-driven tipping points in lake systems.

Table 2: List of cold-monomictic lakes included in the LakeCCI datasets that exhibited at least one mixing anomaly, thus behaved as dimictic, during the period 2000-2022.

#	Id_LakesCCI	Name	Country
1	GLWD00000009	Great Bear	Canada
2	GLWD00000032	Nettiling	Canada
3	GLWD00000495	Portnyagino	Russian Federation
4	GLWD00002540	Nn-Glacial	Greenland
5	HYLA00001784	None	Canada
6	HYLA00002057	None	Canada
7	HYLA00002123	None	Canada
8	HYLA00002892	None	Greenland
9	HYLA00003969	None	Greenland

This approach has broader implications: if successful, it would enable the tracking of thermal regime transitions across the entire continuum of temperate lake types, from cold monomictic to dimictic to warm monomictic systems. Such capability would represent a significant step forward in using EO to monitor and anticipate climate-driven changes in lake mixing behaviour. Moreover, the method may provide a means to differentiate between cold monomictic lakes showing summer mixing anomalies and dimictic lakes with winter anomalies. This distinction could offer insight into whether a lake is in the early stages of destabilization or has crossed a tipping point toward a new thermal regime (Figure 3).

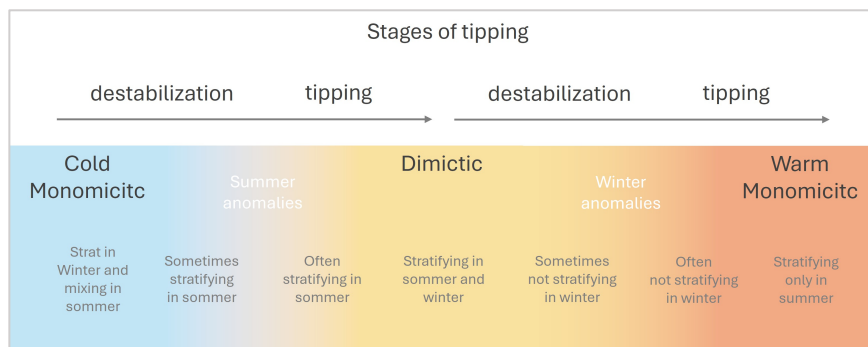


Figure 3: Schematic representation of how temperate lakes (those having their temperature of maximum temperature at $\sim 4^{\circ}\text{C}$) can shift along the cold-monomictic – dimictic – warm-monomictic continuum.

While these results are still preliminary, we plan to investigate them further through expanded analysis and validation. This pilot study has the potential to complement previous work on dimictic lake anomalies, and the results will be incorporated into the web-based visualization portal currently under development, which will provide an interactive platform to explore lake mixing anomalies derived from the LakesCCI dataset in greater detail.

2.4 Further research on remote sensing of thermal bars in lakes

Most cold monomictic lakes currently at risk of shifting toward dimictic regimes are located at high latitudes and are relatively small. As such, they are not represented in the LakesCCI dataset, whose spatial resolution is insufficient to capture their dynamics. To assess whether higher-resolution EO data could address this gap, we tested the use of Landsat thermal imagery for detecting summer mixing anomalies, evaluating whether its lower temporal resolution would still allow reliable tracking.

As a first step, we selected Great Bear Lake as a case study. This large polar lake, classified as cold monomictic and included in LakesCCI, has experienced at least one mixing anomaly in the past two decades. For this lake, we compared Landsat-derived results with those from the 1 km-resolution LakesCCI surface water temperature (SWT) dataset. The objectives of this comparison were twofold:

- 1) To assess whether the two datasets yield consistent results in detecting mixing anomalies.
- 2) To evaluate whether the higher spatial resolution of Landsat could enable extension of the analysis to smaller high-latitude lakes, which are abundant but poorly resolved in LakesCCI.

Great Bear Lake was chosen as a case study because it is one of the cold monomictic lakes where mixing anomalies, years in which the lake exhibited dimictic-like behaviour, were identified using the MixCI analysis applied to LakesCCI data. In parallel, Carmack et al. (2024) recently provided a detailed physical baseline for the lake, describing how surface warming above the temperature of maximum density (TMD) can induce seasonal summer stratification in peripheral arms and shallow nearshore regions. This is followed by autumn overturn and winter inverse stratification, a thermal cycle typical of dimictic lakes. While Great Bear Lake remains classified overall as cold monomictic, this behavior suggests that climate warming may be pushing parts of the lake toward hybrid or transitional mixing regimes.

With a surface area of $\sim 31,000 \text{ km}^2$ and a maximum depth of $\sim 446 \text{ m}$, Great Bear Lake is the largest lake entirely within Canada. Historically, it undergoes a single mixing event each year, occurring after ice-off, when surface temperatures are still below the TMD ($\sim 3.98^{\circ}\text{C}$). The ability to track deviations from this pattern using EO data is thus critical for identifying early signs of regime instability.

We compared the mixing anomalies identified using LakesCCI and Landsat over the last two decades. As shown in Figure 4, out of the six mixing anomalies detected using LakesCCI data, five were also captured using Landsat. The exception was the anomaly in 2021, which was particularly short-lived. The

lower temporal resolution of Landsat likely prevented detection in this case, highlighting a key trade-off between spatial and temporal resolution.

These preliminary results suggest that Landsat thermal data can complement LakesCCI in detecting mixing anomalies, particularly for smaller or narrower lakes that fall below the resolution threshold of LakesCCI. This approach may prove especially useful in polar regions, where such lakes are widespread and particularly sensitive to climate-driven shifts in mixing regimes.

As with the previous pilot, these results remain preliminary, and we plan to expand this analysis further. Importantly, the findings from this polar lake study will be integrated into the web-based visualization platform currently under development, which is designed to support detailed exploration of lake mixing anomalies across multiple datasets, including LakesCCI and Landsat.

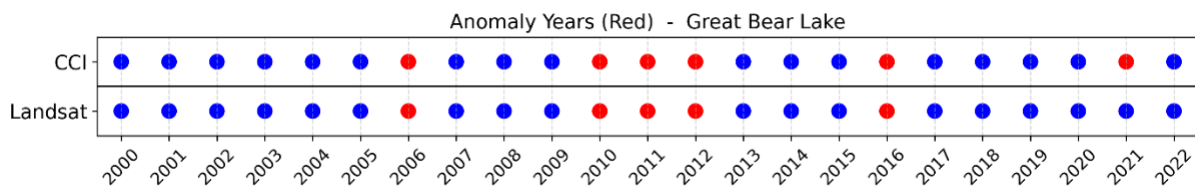
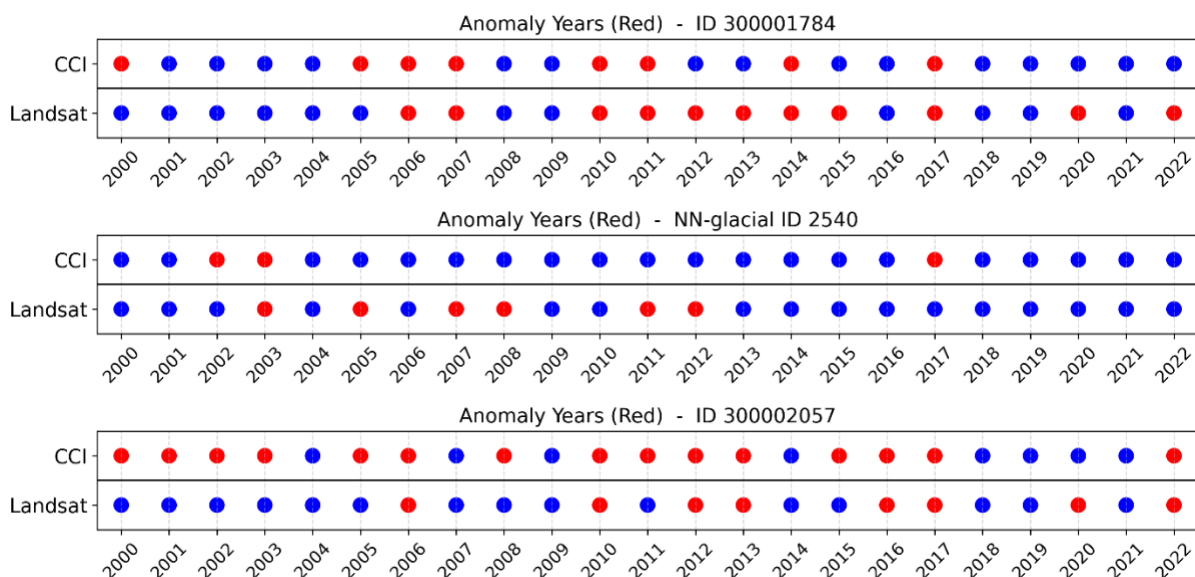


Figure 4: Comparison between the mixing anomalies (red dots) experienced by Great Bear lake and identified by using the MixCi analysed applied to LakesCCI and Landsat data.

We also extended the comparison of mixing anomalies detected by Landsat and lakesCCI to a set of smaller high-latitude lakes (Figure 5). However, in these cases the agreement between the two datasets was significantly lower. This is likely due to two main limitations:

- 1) Sparse spatial coverage in LakesCCI, where smaller lakes are often represented by only a few pixels, which increases uncertainty in the thermal signal
- 2) Reduced temporal coverage in Landsat, which limits the ability to capture short-lived or transient thermal events, particularly in regions with frequent cloud cover.



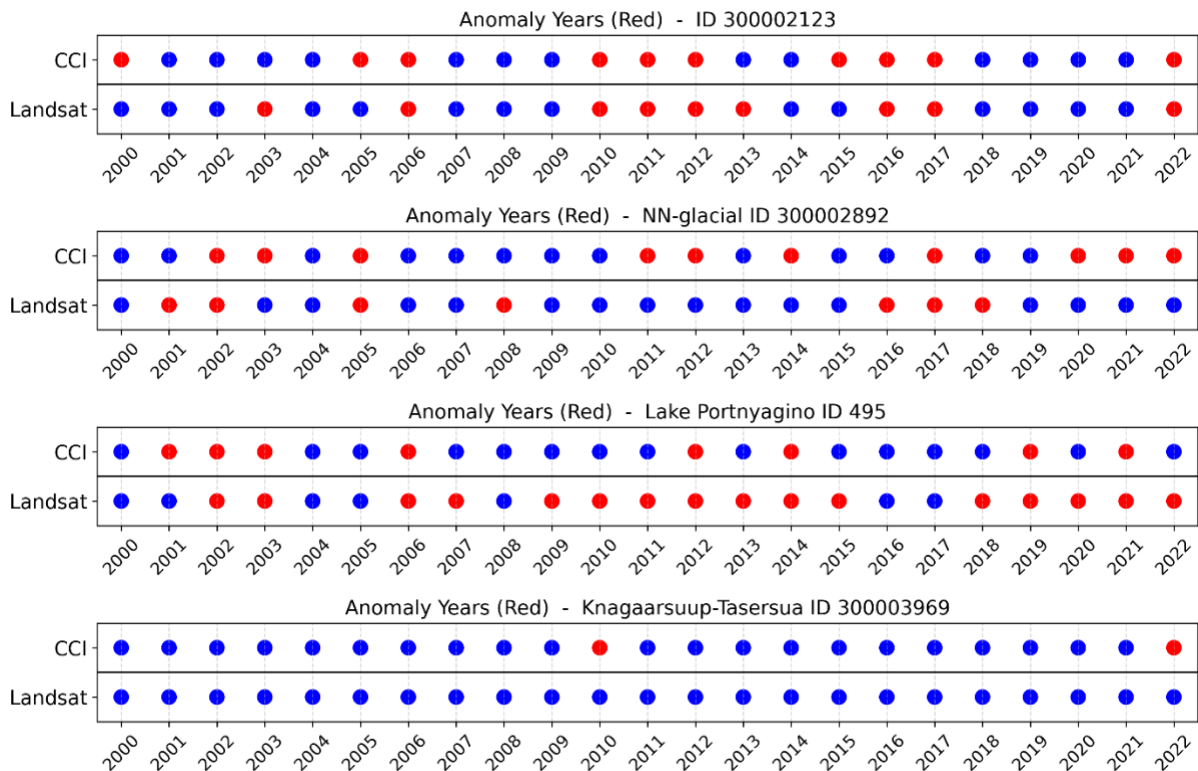


Figure 5: Comparison between the mixing anomalies (red dots) experienced by seven smaller polar lakes and identified by using the MixCi analysed applied to LakesCCI and Landsat data.

These issues highlight the current limitations of both datasets when applied to small polar lakes and suggest that more targeted observation strategies or the integration of multiple EO sources may be required to reliably detect regime shifts in these systems. Nonetheless, these preliminary insights are valuable for understanding the strengths and constraints of existing EO products and we plan to extend the front analyses to other EO products like lake chlorophyll and turbidity.

3 Lake ice cover

3.1 Shifts in lake ice phenology

Tipping in lake ice dynamics occurs when shifts in ice phenology, such as earlier break-up, later freeze-up, or reduced ice thickness, lead to abrupt or persistent changes in the physical and biogeochemical state of lakes (Sharma et al. 2019a; Woolway et al. 2020c). These changes can alter the timing and extent of stratification, influence oxygen and nutrient dynamics, and propagate through the food web, ultimately affecting productivity, greenhouse gas emissions, and ecosystem stability (Bartosiewicz et al. 2019; Hessen et al. 2024).

Satellite observations have revealed that ice cover is particularly sensitive to climate warming, with high-latitude and alpine lakes exhibiting pronounced trends in shortening ice seasons (Pickens et al. 2022; Calamita et al. 2024). Beyond gradual changes, recent analyses highlight nonlinear behaviour in ice phenology. Richardson et al. (2024) demonstrated that interannual variability in ice duration increases as the ice season shortens, but collapses once cover persists for only about a month, signalling a possible approach to an ice-free regime. Similarly, Basu et al. (2024) documented a late-1980s regime shift in Northern Hemisphere lake ice phenology, marking an acceleration in ice loss that continues today. Together, these studies suggest that observed ice shifts are not only indicators of warming but also potential precursor of tipping points in lake physical regimes.

While these findings are strongest for well-monitored regions, they also underscore the vulnerability of smaller and mid-latitude lakes. Such systems are often underrepresented in global datasets yet are likely to experience the most abrupt transitions from seasonal ice cover to intermittent or unreliable freezing (Basu et al. 2024). This gap points to the importance of expanding both in situ and EO-based records to capture the diversity of ice responses across the world's lakes.

3.2 Global lake ice variations and the impact of air temperature

Our review of satellite EO applications demonstrates that multi-decadal and multi-sensor datasets provide powerful tools to track ice cover dynamics (Giardino et al. 2013; Verpoorter et al. 2014). Products from Landsat, Sentinel-2, MODIS, and the LakesCCI project have enabled consistent monitoring of ice-on/off dates, ice duration, and spatial extent at regional to global scales (Pickens et al. 2022; Carrea et al. 2023). These records confirm strong associations between air temperature anomalies and ice phenology, with additional modulation by snow cover, precipitation, and wind forcing (Sun et al. 2018b; Woolway et al. 2021d; c).

Recent global studies highlight the scale of the challenge. Pickens et al. (2022) produced a global assessment of seasonal water and ice dynamics, revealing that nearly two-thirds of inland water surfaces that persist year-round experience seasonal ice cover, yet with high spatiotemporal variability. Basu et al. (2024) Basu et al. (2024) Basu et al. (2024) Basu et al. (2024) Basu et al. (2024) Basu et al. (2024) Basu et al. (2024) Basu et al. (2024) Basu et al. (2024) Basu et al. (2024) Basu et al. (2024) Basu et al. (2024) projected future trajectories for more than one million lakes and showed that under high-emission scenarios, a large fraction may shift from seasonally frozen to intermittently frozen or even ice-free states by the end of the century.

Long-term analyses also point to marked regional differences. For example, Stefanidis et al. (2022) reported a widespread decline in ice thickness across subarctic European lakes, but with strong variability tied to local morphometry and elevation. Similarly, detailed observations from individual systems, such as François Lake in British Columbia, show that thinning or intermittent ice cover can profoundly alter winter mixing and ventilation dynamics (Vagle and Carmack 2023). Such studies demonstrate the ecological importance of winter processes and highlight the consequences of ice loss for year-round lake stability.

Our review of satellite EO applications demonstrates that multi-decadal and multi-sensor datasets provide powerful tools to track ice cover dynamics (Giardino et al. 2013; Verpoorter et al. 2014). Products from Landsat, Sentinel-2, MODIS, and the LakesCCI project have enabled consistent monitoring of ice-on/off dates, ice duration, and spatial extent at regional to global scales (Pickens et al. 2022; Carrea et al. 2023). Studies have highlighted interannual variability in ice phenology and its linkage to air temperature anomalies, snow cover, and wind forcing (Sun et al. 2018a; Woolway et al. 2021a). These EO-derived time series have been used to detect both gradual trends and abrupt shifts in ice cover, making them suitable for identifying early warning signals of lake system tipping (Calamita et al. 2024). Integration with in-situ observations further validates EO products and allows assessment of ecological consequences, including changes in thermal stratification, light availability under ice, and nutrient dynamics (Bartosiewicz et al. 2019; Hessen et al. 2024).

3.3 Knowledge gaps

Despite significant advances in winter limnology and remote sensing, fundamental knowledge gaps persist that limit our capacity to anticipate and interpret tipping behaviour in lake-ice systems. Although some long-term observational records of lake ice phenology exist, they are geographically sparse and largely confined to a handful of well-studied lakes. The vast majority of lakes worldwide remain unmonitored, restricting our ability to detect regional contrasts, validate remote-sensing products, and identify early-warning signals of destabilisation (Basu et al. 2024).

Current monitoring and modelling efforts still rely heavily on binary indicators such as ice-on and ice-off dates. While invaluable for long-term trend analyses, these metrics obscure the sub-seasonal

processes: freeze-thaw cycling, shifts in ice type, gradual changes in ice thickness and rapid break-up events, that often precede destabilisation. Recent reviews highlight the importance of moving towards continuous descriptors of ice conditions (e.g., thickness trajectories, snow-ice interactions, ratios of black to white ice), supported by harmonised definitions and protocols for global interoperability (Sharma et al. 2020; Culpepper et al. 2025).

A particularly critical gap concerns the role of ice quality. Warmer winters increasingly favour the formation of white ice, which alters light penetration, accelerates melt, and has major implications for ecology and human safety. Yet no globally consistent protocol or dataset exists for ice quality, despite growing evidence that a shift towards white-ice-dominated regimes could signal a loss of winter stability (Sharma et al. 2020). Similarly, intra-seasonal freeze-thaw and intermittent ice are widely reported, but detection remains inconsistent, and their ecological impacts remain poorly constrained. Standardised rules for recording such events, combined with high-frequency multi-sensor observations, are urgently needed.

Remote sensing has transformed the monitoring of global ice phenology, but important blind spots remain as ice cover is often just assessed in a 2-dimensional manner. Ice thickness, snow depth and water equivalent, and short-lived break-up events are still difficult to capture from space. Advances in multi-sensor fusion offer promise, but robust uncertainty quantification of these methods is lacking (Culpepper et al. 2025). Long-term analyses across European lakes show significant declines in ice depth, yet reveal strong regional variability tied to morphometry and local conditions (Stefanidis et al. 2022). However, systematic, high-resolution thickness observations remain rare. Without such records, our understanding of thresholds in winter stability and associated ecological consequences remains fragmentary.

Finally, lake ice cannot be considered in isolation from broader ecosystem dynamics. Changing ice regimes feed back onto stratification, nutrient cycling, light availability, and carbon fluxes, and can catalyse abrupt ecological reorganisation (Sharma et al. 2020). Yet explicit frameworks linking observed shifts in ice cover to tipping points in coupled physical-biogeochemical systems are still underdeveloped. Addressing this frontier will require integrating EO, process models and winter limnology, so that we can not only document how lakes are losing their ice, but also anticipate when such losses may trigger irreversible regime shifts in ecosystem function.

3.4 Regional scale lake ice monitoring

Monitoring of ice cover in large lakes has advanced substantially in recent decades. Multi-decadal records from individual lakes and global-scale EO products now allow near-continuous tracking of ice phenology for many larger water bodies, in some cases already approaching the temporal or the spatial requirements set out by the Global Climate Observing System (GCOS) of sub-daily and 50-meter observations, respectively (WMO 2022). Openly available products such as ESA Lakes_cci: Lake products, Version 2.1 (Carrea et al. 2024), deliver over two decades of up to daily lake ice cover data on 1,389 lakes. For small lakes, however, the situation remains different. The spatio-temporal limitations of individual high-resolution sensors mean that single-sensor approaches are unable to provide the dense, consistent time series necessary to resolve ice dynamics at fine scales. As a result, systematic EO-based monitoring of smaller lakes, despite their high abundance and disproportionate role in ecosystem and climate processes, has remained poorly explored.

To address this gap, Brechbühler et al. (in preparation) have developed a multi-sensor fusion approach that combines optical, thermal, and radar satellite data with machine-learning classification techniques. The method integrates a decade of observations (2015 to 2025) from Sentinel-2, Landsat-7/8/9, and Sentinel-1, combining optical, thermal and active microwave data to construct a temporally dense and spatially detailed record of lake ice states across the European Alps. The model framework is trained and validated using ground observations from webcam imagery. Using a deep-learning approach based on Gated Recurrent Unit (GRU) binary semantic classification, each satellite observation pixel is classified as frozen or non-frozen. The resulting outputs are fed into a secondary harmonization GRU model with sensor embedding, which learns sensor-specific weightings and produces consistent ice-

cover time series at approximately 2.5 days effective combined observation frequency and up to 20-meter spatial resolution. Exploiting these outputs yields phenological key metrics for over 1,200 lakes down to a surface area of 5 ha (0.05 km²).

Such fusion-based approaches extend EO capability to small alpine lakes and enable exploratory analyses of sub-seasonal variability and sensitivity to meteorological and morphometric drivers, while advancing towards GCOS goal requirements for both spatial resolution and temporal frequency. More broadly, regional-scale high-resolution monitoring provides a means to bridge the gap between global ice phenology products, which remain biased toward large lakes, and sparse local in situ observations that capture fine-scale processes. Importantly, this capability also strengthens our ability to detect early-warning signals of tipping behaviour, as small lakes are often the first to experience abrupt loss of ice cover.

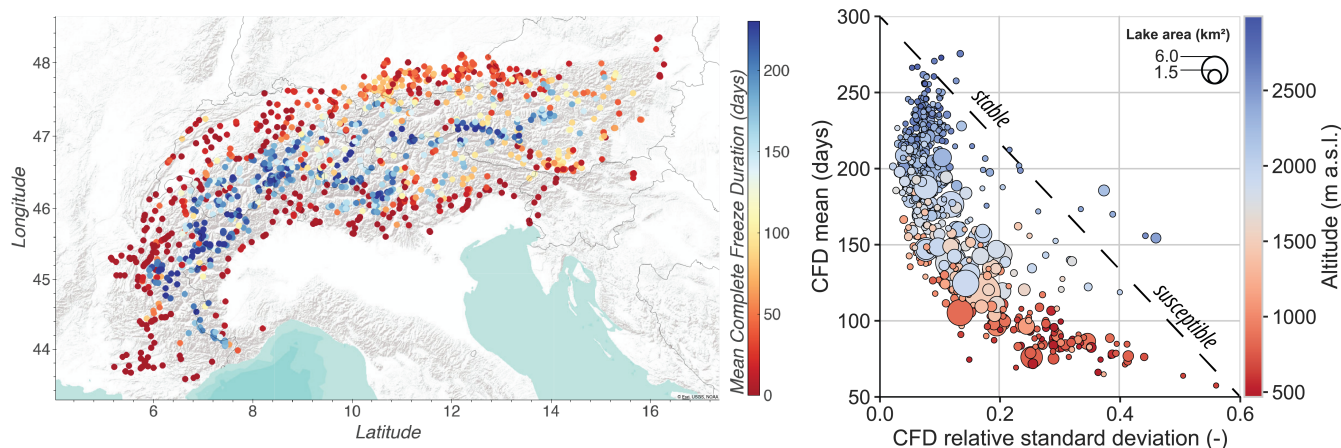


Figure 6: Length of lake ice cover in the European Alps 2016-2025 (left) and associated susceptibility to ice loss (right) (Brechtbühler et al. in preparation).

Preliminary results illustrate the potential of this framework. For example, aggregate lake ice coverage across the European Alps can be quantified for the last decade as per-lake averaged complete freeze duration (CFD) to visualize differences in temporal extent of ice cover (Figure 6, left). The resulting ice phenology can also be used to investigate susceptibility to ice loss. Figure 6 (right) shows mean CFD against the relative standard deviation of yearly CFD, an indicator of variability, and reveals an “ice-loss susceptibility space”. Lakes occupying the lower-right quadrant, characterised by short ice seasons and high interannual variability, emerge as particularly vulnerable to future abrupt losses of ice cover and winter stability.

4 Lake browning

4.1 Drivers and impacts of lake brownification

Lakes play an important role in regulating the carbon cycle, acting as both sinks (through sedimentary carbon burial) and sources (degradation and resulting mineralisation to CH₄, CO and CO₂) for carbon. The phenomenon of lake brownification, referring to the long-term increase in water colour from dissolved organic carbon (DOC), has the potential to significantly reshape this role. DOC can have widespread impact on a lake’s ecological, biogeochemical, and limnological properties (Kritzberg et al. 2020) and yet is considered an understudied component of the carbon cycle in large lakes, despite its relevance to the Earth’s biogeochemistry and climate (Minor and Oyler 2023). By increasing the absorption of solar radiation at the lake’s surface, high DOC concentrations reduce light penetration and availability for primary production, altering phytoplankton communities, biodiversity and food web structure (Seekell et al. 2015; Williamson et al. 2015a; Urrutia-Cordero et al. 2017). DOC-related light

attenuation and associated surface water warming can alter the mixed layer depth, strengthen stratification and reduce heat penetration resulting in cooler hypolimnia (Read and Rose 2013; Williamson et al. 2014; Strock et al. 2016), with potential for shifts in mixing regimes (Woolway and Merchant 2019), increasing hypoxia (Brothers et al. 2014; Knoll et al. 2018) and altered carbon cycling pathways. DOC-rich systems can become net sources of atmospheric carbon (Tranvik et al. 2009; Bastviken et al. 2011) therefore lake browning reflects a significant positive feedback mechanism to the earth's climate.

Lake browning is driven by a combination of climate, hydrological and watershed processes. Increased precipitation leads to higher runoff, mobilizing organic matter from soils into lakes (Kritzberg et al. 2014), while rising temperatures enhance soil microbial activity, increasing DOC production and mobility (Jennings et al. 2009; Wen et al. 2020). Soil recovery from acidification following the reduction in anthropogenic sulphur emissions is a key watershed driver of rising DOC in historically acidified regions (Evans et al. 2006; Monteith et al. 2007). Winter snowpack, changes in snowfall dynamics, melting permafrost as well as hydrological connectivity, land cover, land use, and catchment greening have also been highlighted as key factors driving DOC fluxes (Laudon et al. 2011; Blanchet et al. 2020; Meingast et al. 2020). (Finstad et al. 2016) examined time-series data from 70 Norwegian lakes and catchments over a 30-year period, and showed that increasing vegetation cover, alongside reduced sulphate deposition, temperature rises, and increased runoff, significantly contributed to rising DOC concentrations in those lakes. (Meyer-Jacob et al. 2019) showed that Canadian lakes which had experienced heavy acid deposition are now undergoing re-browning, returning toward historical DOC levels, whereas in low-deposition areas, climate-driven changes are causing DOC to surpass past levels, with new ecological states emerging.

4.2 Status of lake browning and potential tipping points

Increasing concentrations of DOC have been well documented in freshwater systems across temperate latitudes and boreal regions of Europe, North America, and parts of Asia. Long-term monitoring in Scandinavia has shown marked increases in DOC concentrations since the 1980s (Monteith et al. 2007; Couture et al. 2012). Similar trends are evident in North America, where lakes in Ontario, Minnesota, and the northeastern U.S. have shown consistent browning (Stoddard et al. 1999; Solomon et al. 2015). In contrast, some alpine and Arctic lakes exhibit stable or declining DOC, highlighting significant spatial variability and the importance of local catchment and in-lake processes (Tanentzap et al. 2008; Williamson et al. 2015b).

Most regional studies, and even global assessments, of the status of lake DOC and browning trends have relied primarily upon in situ data. (Toming et al. 2020) combined machine learning, the HydroLAKES and WorldClim databases and globally distributed in situ DOC concentrations to understand climate and watershed drivers of lake DOC and predict DOC in lakes globally (Figure 7). Meyer-Jacob et al. (2019) analysed historical sedimentary records and long-term in situ water chemistry monitoring programs for trend analysis. Finstad et al. leveraged satellite-derived NDVI as a proxy for terrestrial greening to capture long-term vegetation trends but relied on in-lake DOC observations to track browning. (Blanchet et al. 2022) reviewed the global extent and implications of browning and identified key research gaps, including expanding the use of remote sensing to investigate browning and its ecological and climate impacts from local to global scales. Monitoring data remains sparse in large parts of the world's lakes, including in tropical, southern hemisphere, and high-altitude lakes, limiting global assessments. There remains a gap, therefore, in applying satellite remote sensing products to understand long-term trends in lake browning at a global scale particularly as it relates to the impact on shifting thermal regimes and potential tipping points. Knowledge gaps exist on the extent to which browning alters lake carbon fluxes and greenhouse gas emissions, and how future climate change will interact with land cover dynamics to shape long-term trends, with opportunities for integrated models linking terrestrial inputs, lake processes, and climate drivers.

The metabolic balance of lakes is strongly influenced by DOC (Hanson et al. 2003). Lakes with low DOC concentrations, typical of clear, oligotrophic conditions, have a tendency toward autotrophy and may act as net CO₂ sinks, drawing down atmospheric CO₂ through net primary production. In contrast, dark, high-DOC lakes are typically heterotrophic and supersaturated with CO₂ and hence function as sources of CO₂ to the atmosphere (Sobek et al. 2003, 2005; Duarte and Prairie 2005). These patterns reflect a fundamental potential carbon tipping point where rising DOC concentrations may shift systems from net autotrophy to net heterotrophy, altering regional carbon budgets and feedbacks to the atmosphere (Sobek et al. 2003; Lapierre et al. 2013; Solomon et al. 2015). There is ample empirical evidence of a positive relationship between lake DOC concentrations and carbon fluxes across the air-water interface (Sobek et al. 2003; Lapierre et al. 2013; Solomon et al. 2015). DOC concentrations have been shown to be the best predictor of pCO₂ and thus of the degree of heterotrophy in boreal lakes (Sobek et al., 2003), with DOC acting as a significant regulator of lake fluxes even on a global scale (Sobek et al., 2005). Prairie et al. (2002) showed that metabolic gas balances could be predicted from DOC concentrations, with concentrations between 4 and 6 mg L⁻¹ DOC corresponding to metabolic equilibrium, whereas Hanson et al. (2003) documented the divergence between autotrophy and heterotrophy occurring at DOC concentrations of 10 mg L. Seekell et al. (2015) also noted a threshold DOC concentration of 4.8 mg L⁻¹ below which the DOC-primary production relationship is positive, and above which the relationship is negative. It is likely that the threshold, and therefore an exact tipping point, is not fixed but modulated by regional variations in nutrients, mixing regime, and light conditions (Solomon et al., 2015). Nevertheless, relative change in lake DOC captured by continuous long-term records of satellite-derived CDOM could be indicative of such tipping points in lake metabolism and their feedback to the climate.

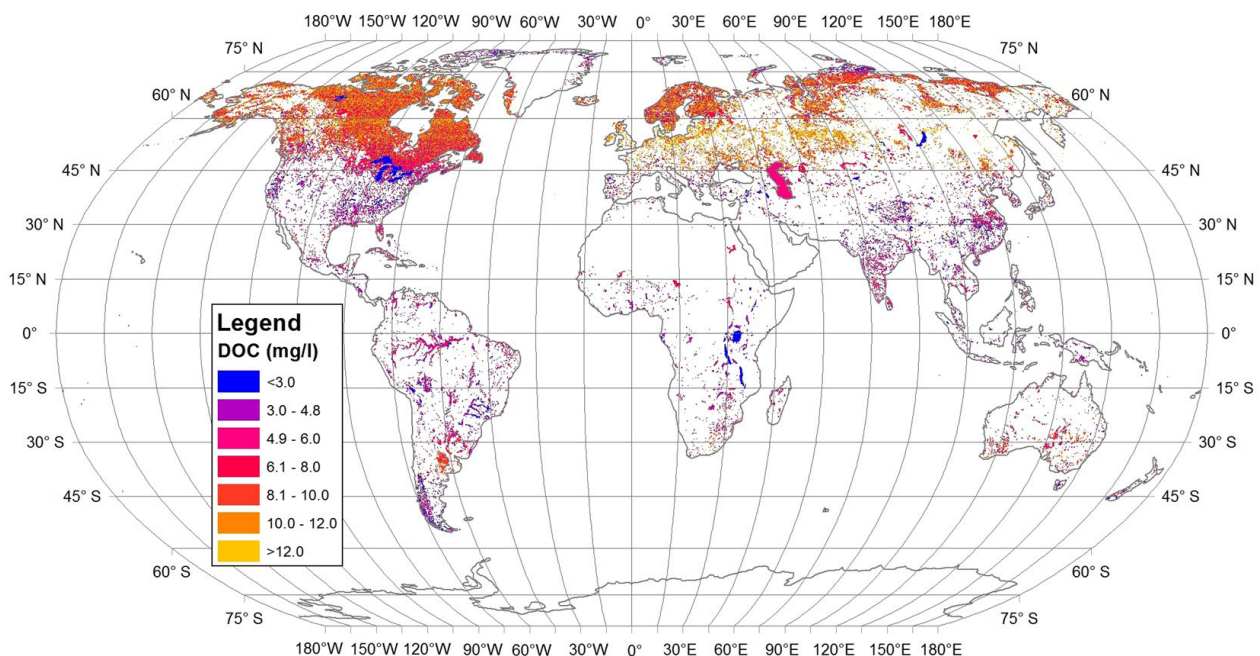


Figure 7: DOC concentrations of global lakes, from Toming et al. (2020).

4.3 Satellite Remote Sensing of Lake DOC

Satellite remote sensing has greatly advanced the ability to map large-scale variations in lake DOC and determine lake browning trends using coloured dissolved organic matter (CDOM) as a spectral proxy. A portion of DOC is optically inactive; therefore, lake DOC content cannot be mapped directly (Toming

et al. 2016). Retrievals of DOC concentrations therefore rely on empirical relationships between CDOM and total DOC. In freshwater ecosystems, CDOM absorption properties have been found to be highly correlated with DOC concentrations (Massicotte et al. 2017) although significant variability exists both temporally and spatially among lake ecosystems (Fichot et al. 2023; Rodríguez-Cardona et al. 2023). For example, Toming et al. (2016) noted that CDOM did not appear to be a good predictor of the seasonality of DOC concentration in Lake Võrtsjärv, Estonia, since the CDOM-DOC coupling varied seasonally. However, combining the data from Võrtsjärv with data from six other eutrophic lakes in the world showed that CDOM was the most powerful predictor of DOC and can be used in remote sensing of DOC concentrations in eutrophic lakes. Võrtsjärv with data from six other eutrophic lakes in the world showed that CDOM was the most powerful predictor of DOC and can be used in remote sensing of DOC concentrations in eutrophic lakes.

Remote sensing of CDOM relies on its strong absorption of blue and ultraviolet wavelengths and resulting impact on the spectral shape of remote sensing reflectance. Empirical approaches typically apply band ratios (e.g. blue to green or blue to red reflectance ratios) calibrated against in situ CDOM absorption to generate regionally applicable retrieval algorithms (Kutser et al. 2009; Brezonik et al. 2015). Semi-analytical and bio-optical inversion methods, such as the Quasi-Analytical Algorithm (QAA), decompose reflectance into inherent optical properties to separate CDOM (and detrital matter) from phytoplankton pigments, improving transferability across lakes with varying optical conditions (Carder et al. 2002; Zhu et al. 2014), while more recently machine learning approaches act to simultaneously retrieve multiple water constituents, including CDOM, in an effort to reduce retrieval uncertainties in optically complex waters (Pahlevan et al. 2022). Nevertheless, challenges remain in obtaining reliable and consistent retrievals across diverse and optically complex lake types. Remote sensing of the highest range of CDOM and DOC concentrations in black waters, for example, remains very challenging and subject to large uncertainties due to the extremely low water-leaving radiance (Kutser et al. 2016).

Remote sensing has enabled regional-scale mapping of CDOM in Finnish and Estonian lakes using Sentinel-2 (MSI), Landsat, and the Advanced Land Imager (ALI) (Kutser et al. 2016; Toming et al. 2016). For example, Kutser et al. (2009) used ALI to study regional variations in-lake CDOM, DOC and CO₂ saturation across southern Finland. Most case studies assessing the feasibility of retrieving DOC concentration with remote sensing have been on single or a small selection of lakes (Chen et al. 2017; Li et al. 2018), with some larger regional scale studies (Olmanson et al. 2020; Liu et al. 2021). High spatial resolution sensors have proven successful for CDOM mapping of smaller waterbodies but datasets often lack the temporal range to allow trend and regime shift detection. OC-CCI products aim to deliver the required continuous long-term data suitable for trend assessments. The OC-CCI dataset has been used to determine browning trends in the World's largest lakes over the 1997–2023 period (Kutser and Soomets 2024). Further preliminary analysis of OC-CCI summer a_{g412} (absorption coefficient of dissolve and detrital material) anomalies for a selection of north American lakes, captured browning trends in some northern lakes, and declining DOM in the Laurentian Great Lakes, likely attributed to the impacts of oligotrophication and invasive zebra mussels. These case studies demonstrate the potential for both regional trend detection and global assessments of lake browning using optical remote sensing. However, the spatial resolution of OC-CCI products limit their use on the vast majority of global lakes. The Lakes_cci project does not currently deliver CDOM products because globally validated algorithms with acceptable uncertainties are lacking. The Lakes_cci Phase 2 conducted a CDOM algorithm round-robin exercise and tuning in an optical-water-type (OWT) framework using largescale in situ Rrs datasets (Limnades, GLORIA) (ESA, 2022). 16 algorithms were selected for the assessment of $a_{CDOM(440)}$ estimation (Figure 8), including empirically calibrated band ratios (Mannino et al. 2008, 2014; Ficek et al. 2011; Brezonik et al. 2015) semi-analytical (Zhu and Yu 2013) and machine learning (Pahlevan et al. 2022) approaches. Results highlight that gaps remain, with remote sensing algorithms often requiring local calibration to handle optical complexity and varying optical water types.

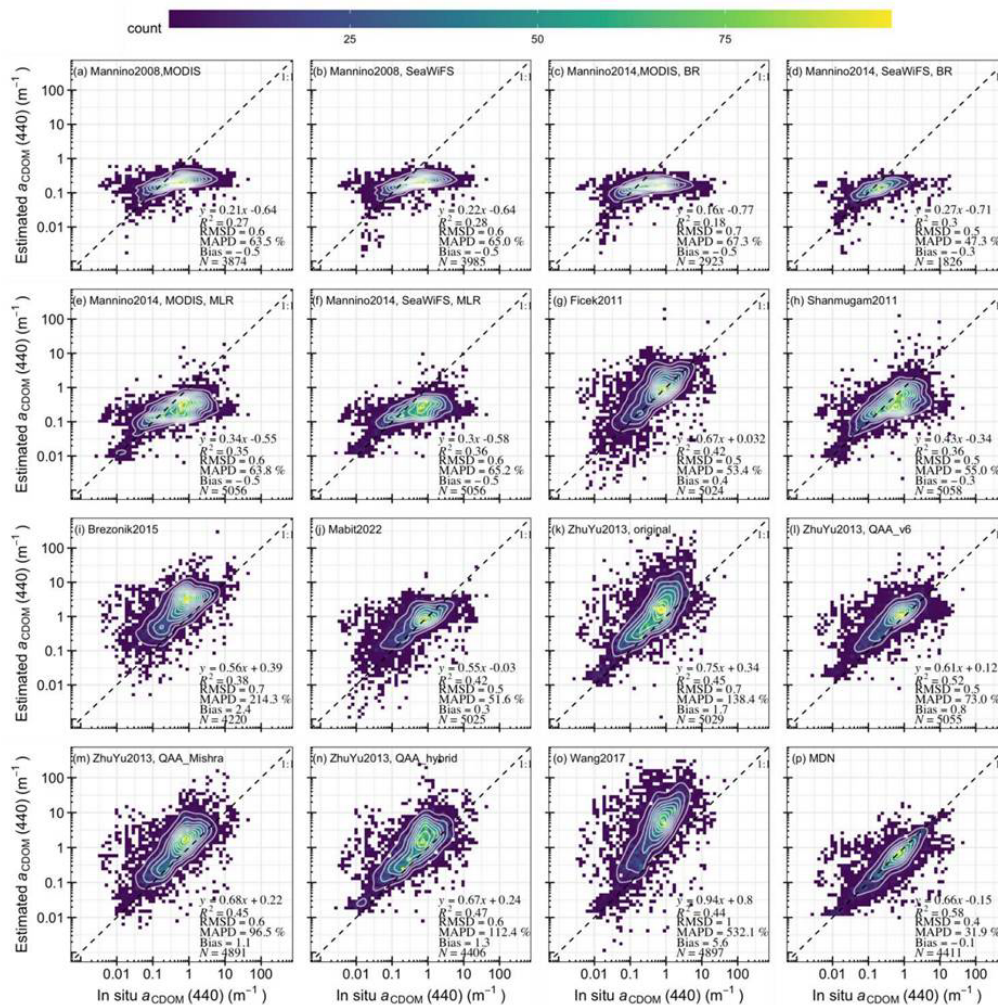


Figure 8: Comparison between in situ and estimated $a_{CDOM(440)}$ using previously published algorithms. Colour and white lines indicate the density of data points. (ESA technical note, 2022)

5 Plankton phenology

5.1 What is tipping?

Tipping in lake mixing regimes, or shifts in lake mixing phenology, can drive changes in lake productivity. Alterations in the timing, duration, or intensity of thermal stratification affect nutrient distribution, light availability, and oxygen dynamics, which in turn influence the growth and composition of phytoplankton and other primary producers. Consequently, changes in mixing regimes can propagate through the food web, altering ecosystem structure and function.

5.2 Preliminary work

Several previous studies have investigated phytoplankton phenology in individual lakes (Palmer et al. 2015; Ma et al. 2022; Toussaint et al. 2025). But unlike phenology of terrestrial ecosystems (e.g., NASA's MCD12Q2 product), no global phytoplankton phenology product is available today. However, for ESA Lake CCI CCN 9, Eawag is currently compiling such a dataset based on daily Lake CCI chlorophyll-a and cyanobacteria index products, using a new phenology retrieval algorithm (Lever 2025). As in MCD12Q2, the retrieval of phenology metrics is based on a pixelwise cubic spline fit function across a

multiyear time series. In addition, the algorithm clusters pixels with similar phenology into blooms. Because unlike the single productive cycle in polar lakes (and most terrestrial vegetation), temperate and subtropic lakes experience up to three blooms per year. Our preliminary results based on Lakes CCI v2.0 products and an earlier version of the phenology retrieval algorithm demonstrate that EO data can effectively track algal bloom dynamics (<https://www.bgbphenology.com/>).

The new Lakes CCI phenology products will only be finalized during RESETlakes WP2, which is why no preliminary analyses were performed in WP1. As soon as the products are completed, we will perform further analyses starting with lakes that experienced multiple mixing anomalies in recent years.

5.3 Knowledge gaps

While EO can separately track mixing phenology and algal blooms, the relationship between these processes remains poorly quantified. If the spatial patterns of lake surface water temperature (LSWT) can be used to identify the timing and strength of mixing and stratification phases, their combination with chlorophyll-a (Chl-a) data could provide valuable insights into how physical mixing influences lake productivity. For instance, stronger mixing events may enhance nutrient resuspension from deeper layers into the euphotic zone, promoting algal growth, whereas prolonged stratification could limit nutrient availability and suppress productivity. Establishing and monitoring this link would allow the use of near-real-time EO observations to infer the intensity of mixing events and their biogeochemical consequences. Ultimately, such an integrated EO approach could underpin the development of early-warning systems for shifts in lake productivity, supporting proactive ecosystem management and mitigation of harmful algal bloom events.

5.4 Potential contribution from EO.

Observation can provide critical data to link lake mixing phenology with algal bloom dynamics. EO-derived surface temperature and ice cover measurements allow monitoring of stratification onset, duration, and overturn across multiple lakes and seasons. High-resolution optical and multispectral data (e.g., Sentinel-2, Landsat, PlanetScope) enable tracking of chlorophyll-a, turbidity, and water color changes, capturing bloom intensity and spatial distribution. By integrating these physical and biological indicators, EO can reveal causal relationships between mixing patterns and productivity shifts. Furthermore, near-real-time EO observations can feed early-warning systems for harmful algal blooms, complementing in situ monitoring and modeling efforts to support proactive lake management and ecosystem conservation.

6 Combined seasonal lake processes

6.1 Links between ice, stratification and phytoplankton phenology

Tipping in lakes refers to abrupt, often nonlinear changes in ecosystem state that occur when gradual or compounding pressures exceed critical thresholds, producing shifts that are difficult or impossible to reverse. Traditionally, studies of tipping have focused on individual processes. For example, many lakes that once froze reliably every winter now experience intermittent or absent ice cover, with a growing number projected to lose seasonal ice altogether under continued warming (Sharma et al. 2019b). Similarly, some lakes are crossing extreme thermal thresholds, leading to conditions where temperatures once considered anomalous now persist permanently (Woolway et al. 2021b). These thresholds relate not only to biological tolerance limits but also to key physical transitions. For example, (Woolway et al. 2019) how that in a set of eight well-monitored European lakes the annual minimum surface water temperature increased by on average $+0.35\text{ }^{\circ}\text{C decade}^{-1}$ from 1973-2014. In several of these lakes the minimum no longer reaches the $\sim 4\text{ }^{\circ}\text{C}$ mark — the temperature of maximum density for freshwater — meaning that deep-mixing processes during winter are inhibited (e.g., the stratification “reset” doesn’t occur). Crossing this $\sim 4\text{ }^{\circ}\text{C}$ threshold thus marks a physical tipping point: a lake avoids cooling sufficiently to trigger the usual homothermy and full overturn, which then has knock-on effects

for oxygenation, nutrient transport, and cold-water species habitat. Biological tipping has also been documented, such as the poleward expansion of algal blooms, with northern lakes that historically did not host blooms now experiencing them on a regular basis (Pick 2016; Favot et al. 2019).

The concept of combined phenology recognises that such thresholds rarely operate in isolation. Instead, tipping emerges from the interconnected timing of multiple physical and biological processes. Ice cover, thermal stratification, water column mixing, primary productivity, algal bloom development, and lake browning form a tightly coupled seasonal sequence. Disruptions in the timing of one component cascade through the system, creating the potential for systemic tipping. Earlier ice-off, for instance, shortens the winter dormancy period, lengthens the open-water season, and advances the onset of stratification (Austin and Colman 2007; Woolway and Merchant 2017). These changes alter nutrient redistribution, light conditions, and oxygen dynamics (Jane et al. 2023). If prolonged stratification coincides with high summer temperatures, oxygen depletion in the hypolimnion can intensify, leading to fish kills or favouring species that tolerate low oxygen (Till et al. 2019). Increased inputs of dissolved organic matter (DOM) from surrounding catchments further modify this trajectory. Browning reduces underwater light penetration, weakens benthic primary production, and shifts energy pathways toward phytoplankton-dominated systems (Koizumi et al. 2023; Jane et al. 2024). Once such shifts occur, reinforcing feedbacks such as hypoxia-induced nutrient release or bloom-driven self-shading can lock lakes into new, less desirable ecological regimes.

These risks are amplified when multiple stressors interact in what are known as compound events (Woolway et al. 2025). Compound events occur when extremes co-occur, follow sequentially, or interact across space, leading to disproportionately large impacts relative to individual events. For example, a drought may reduce lake levels and concentrate nutrients, followed by floods that flush in large amounts of organic matter, and then a heatwave that enhances stratification and oxygen depletion. Such a sequence can result in abrupt whole-lake anoxia or persistent harmful algal blooms. These impacts are not simply additive; they emerge from the nonlinear coupling of physical, chemical, and biological processes.

The review of extreme events in lakes (Woolway et al. 2025) highlights several categories of stressors that drive these dynamics. Lake heatwaves, defined as prolonged periods of anomalously high water temperatures, are becoming more frequent and intense, often reinforcing stratification and driving hypoxia (Zhang et al. 2025). Hydrological extremes, including droughts and floods, reshape lake levels and water residence times, altering nutrient cycling and habitat availability. Underwater dimming events, driven by floods, storms, or browning, sharply reduce light penetration, destabilising primary production and promoting shifts from macrophyte-dominated to phytoplankton-dominated states. Finally, hypolimnetic hypoxia, defined as prolonged depletion of oxygen in bottom waters, arises from stratification, heatwaves, and organic matter loading, with cascading consequences for biodiversity and biogeochemical cycling.

Crucially, these univariate extremes often interact to form compound events. For example, concurrent heatwaves and droughts shrink the oxythermal habitat available to fish, pushing species beyond tolerance limits. Sequential drought–flood–heatwave episodes can drive massive organic matter inputs followed by rapid decomposition, leading to whole-lake oxygen collapse. Spatially connected events, such as flood pulses moving through a chain of interconnected lakes, can transfer carbon and nutrients downstream, propagating impacts across landscapes. These examples underscore that tipping in combined phenology is rarely driven by one factor alone, but instead by the timing and interaction of multiple stressors.

The study of combined phenology therefore demands an integrated framework that links timing, thresholds, and feedbacks across physical, chemical, and biological processes. Only by recognising the cascading nature of tipping, where one phenological shift triggers or amplifies others, can we understand and anticipate the systemic changes now unfolding in lakes worldwide.

6.2 Preliminary work

Research over the past decades has laid a strong foundation for understanding the individual and interconnected components of lake phenology. Observations of ice cover dynamics are among the longest available, with many northern lakes showing dramatic reductions in seasonal ice duration over the twentieth and twenty-first centuries. Satellite data have confirmed widespread shifts toward earlier ice-off and later freeze-up. Such changes extend the warm season and amplify risks of extreme thermal events. Loss of ice cover itself can represent a tipping point, with lakes that previously froze reliably every year now experiencing intermittent freezing, altering their thermal regimes and downstream ecological processes (Sharma et al. 2019b).

Thermal stratification and surface water temperature have been studied using both in situ monitoring and remote sensing. In-situ monitoring data have provided critical insight into stratification onset and breakdown (Woolway et al. 2021a). These observations align with satellite-derived temperature products, which provide a large-scale context and demonstrate the intensification of lake heatwaves in many regions (Woolway et al. 2021a). Stratification dynamics are also closely tied to evaporation, which in turn affects water levels. As demonstrated in (Woolway et al. 2020b), ice cover, stratification, surface temperature, and evaporation interact in ways that can drive substantial changes in water balance. Figure 4 from that review illustrates how shifts in these individual variables, if pushed beyond thresholds, can cascade into drastic changes in lake water availability, a clear example of how tipping in one process propagates through the system (Figure 9).

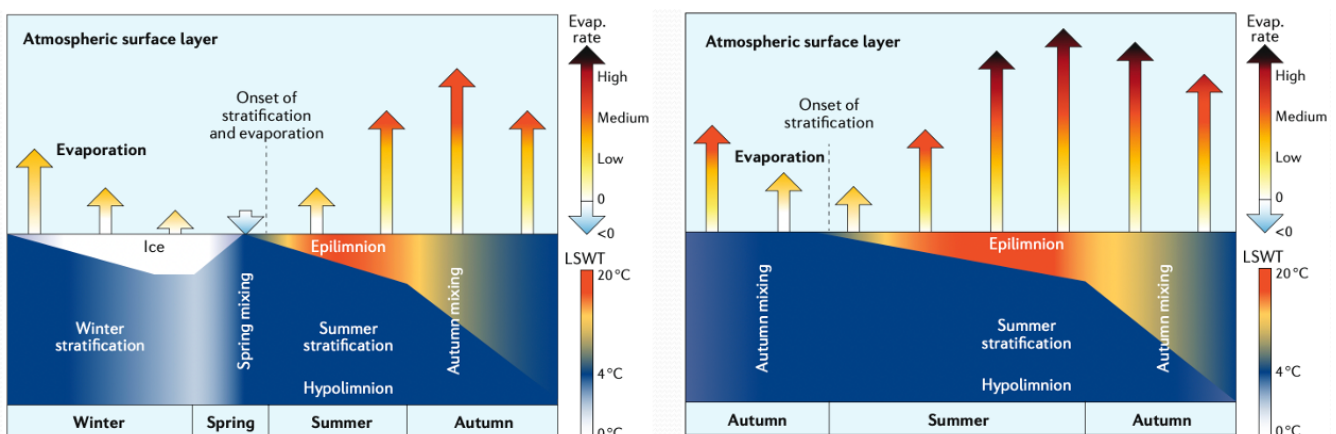


Figure 9: Conceptual diagram showing interactions among ice cover, surface water temperature, stratification, and evaporation, and how tipping in individual variables can propagate into changes in water availability (adapted from Woolway et al. 2020). These are shown under historic (left) and future (right) conditions.

Primary productivity and bloom phenology have likewise been studied using both in situ and EO data. The BGBPhenology project showed that multispectral sensors can effectively track bloom onset, intensity, and decline across diverse lakes. These findings highlight the feasibility of linking biological responses to physical regime shifts, such as earlier stratification leading to advanced bloom timing. In some cases, such shifts represent tipping behaviour, as seen in the poleward expansion of annual algal blooms into lakes that previously did not host them. Browning has also emerged as an important driver, with increases in dissolved organic matter inputs altering underwater light regimes and suppressing benthic production. In extreme cases, sudden inflows of organic matter following floods can trigger “underwater dimming” events that shift ecosystems from macrophyte-dominated to phytoplankton-dominated states (Woolway et al. 2025).

In addition to observational work, modelling approaches have played a central role in advancing understanding of lake phenology. Process-based models such as the General Lake Model (GLM) and MyLake have been widely used to simulate stratification, mixing, and biogeochemical dynamics under historical and projected climate conditions (Saloranta and Andersen 2007; Hipsey et al. 2019). These

models provide mechanistic insight into how physical drivers propagate through ecosystems. Complementing them, statistical models have been applied to derive empirical relationships between climate drivers and phenological outcomes, offering useful predictive tools. More recently, machine learning methods, including long short-term memory (LSTM) networks, have been used to capture nonlinearities and temporal dependencies in lake dynamics (Piccolroaz et al. 2024). These methods show particular promise for forecasting tipping events because of their capacity to integrate multiple variables and large datasets.

Together, these efforts show that ice cover, stratification, surface temperature, evaporation, productivity, blooms, and browning are interdependent processes whose timing and feedbacks shape the resilience of lake ecosystems. The integration of EO, process-based modelling, and emerging machine learning approaches now provides an unprecedented opportunity to investigate tipping behaviour not only in isolated variables but across the combined phenology of lakes.

6.3 Knowledge gaps

Despite substantial progress in monitoring and modelling individual components of lake phenology, critical knowledge gaps remain that limit our ability to anticipate tipping behaviour in combined systems. These can be grouped into four categories: physical, biogeochemical, biological, and methodological.

Physical gaps. One key gap lies in quantifying causal linkages between stages of the seasonal cycle. While earlier ice-off is known to advance stratification onset, the precise thresholds, sensitivities, and lag effects of this relationship remain poorly constrained across different lake types. Stratification–evaporation interactions, which are central to water balance and water availability, are also not well quantified globally.

Biogeochemical gaps. Although hypoxia-induced phosphorus release is well documented, its role in triggering recurrent bloom dominance under compound stress remains insufficiently quantified. Similarly, the extent to which browning consistently suppresses or, under some conditions, promotes phytoplankton growth is poorly understood at the global scale.

Biological gaps. The expansion of blooms into previously unaffected lakes is a clear example of tipping, but the biological thresholds governing such transitions are still uncertain. Cross-scale generalisation is also difficult: small, dimictic boreal lakes respond very differently to warming and nutrient pulses than large, polymictic tropical systems. Developing typologies of lakes that capture shared sensitivities remains an urgent task.

Methodological gaps. Perhaps the most significant limitation concerns our ability to project future change. Process-based models such as GLM, FLake and MyLake are powerful tools, but their reliability depends on robust validation. To build confidence in future projections, models must first be run in hindcast mode, demonstrating their capacity to reproduce known historical events such as the 2003 and 2018 European heatwaves (Woolway et al. 2020a). Complementary approaches such as statistical modelling and machine learning (e.g., LSTM networks) are increasingly applied, but they too require validation and are prone to overfitting.

A particularly promising avenue is the use of process-guided deep learning, which combines the mechanistic insight of process-based models with the pattern-recognition strengths of machine learning. In this approach, physical constraints from lake models (e.g., energy balance, stratification physics, oxygen dynamics) are embedded into neural networks, guiding the learning process and preventing implausible predictions. This helps machine learning models generalise to novel conditions while taking full advantage of the increasing availability of EO datasets. By assimilating EO-derived ice cover, surface temperature, bloom dynamics, and browning signals, process-guided deep learning frameworks could provide more robust, transferable predictions of tipping behaviour in combined phenology than either approach alone.

Finally, early-warning indicators of tipping are underdeveloped. While theory suggests that statistical signals such as increasing variance, rising autocorrelation, or changes in skewness may herald

impending regime shifts, their application to lake systems has been limited. Integrating EO time-series analysis with early-warning frameworks, and embedding these within process-guided deep learning systems, could provide powerful tools for anticipating tipping.

6.4 Potential contribution from EO

Earth Observation (EO) has the potential to transform our ability to detect, monitor, and ultimately forecast tipping in combined lake phenology. Its strength lies not only in providing consistent global coverage but also in enabling the integration of multiple phenological variables at spatial and temporal scales unachievable by in situ methods alone. However, doing so requires overcoming the challenge of aligning data across different missions, sensors, and temporal archives. Since tipping in combined phenology depends on the synchronisation of processes (e.g., ice-off leading to earlier stratification, which subsequently advances bloom onset), EO records of different variables must be harmonised. If satellite-derived temperature records show a shift in stratification timing but chlorophyll-a records from another mission are misaligned due to sensor differences, then the cascading nature of tipping risks may be obscured. Ensuring consistency across missions, both in terms of calibration and temporal overlap, is therefore a critical task for EO applications in this field.

For ice and surface water temperature, EO datasets such as MODIS, VIIRS, and Sentinel-3 provide long-term, high-frequency records that allow robust assessment of freeze–thaw timing, surface anomalies, and lake heatwaves. These datasets form the foundation for linking thermal dynamics with subsequent biological responses. Stratification, although difficult to measure directly, can be inferred from EO-derived surface warming patterns, particularly when surface temperatures cross the density maximum of freshwater (Austin and Colman, 2008; Woolway and Merchant, 2017), implying that stable stratification has begun. When coupled with hydrodynamic models such as GLM, these EO datasets allow spatially explicit estimates of stratification onset, breakdown, and duration. New satellite altimetry missions such as SWOT add another layer of information, linking hydrological variability with thermal and mixing dynamics and illuminating pathways to tipping in water availability. Yet harmonising the temporal and spatial resolution of these datasets remains a major challenge: MODIS provides daily coverage but at coarse resolution, Sentinel-2 provides fine resolution but at lower frequency, and SWOT altimetry offers yet another sampling pattern. Integrating these into a coherent picture of phenology requires careful cross-calibration and data fusion.

For primary productivity and algal blooms, EO already provides indispensable information. High-resolution sensors such as Sentinel-2, Landsat, and PlanetScope allow mapping of chlorophyll-a, turbidity, and bloom extent with exceptional spatial detail, while Sentinel-3 OLCI offers near-daily global coverage. Together, these datasets can capture bloom timing, intensity, and recurrence, providing indicators of biological tipping such as the establishment of annual blooms in lakes that historically remained bloom-free. The challenge here is again one of alignment: Sentinel-2 and Landsat provide long historical records, but with different band configurations and revisit frequencies, making intercomparison difficult. Without harmonisation, a tipping signal observed in bloom frequency from one record may not be directly traceable in another, complicating assessments of combined phenology.

Browning and underwater dimming, though less well developed in EO applications, are increasingly tractable using water colour indices, CDOM proxies, and emerging hyperspectral data. These products make it possible to track both chronic browning trends and episodic flood-driven pulses of organic matter, which are critical for linking catchment events with in-lake light limitation and productivity shifts. Here, consistency is particularly challenging because many water colour algorithms are sensor-specific. For instance, algorithms developed for MODIS cannot always be applied directly to Sentinel-2 or hyperspectral sensors without recalibration. This makes it difficult to build long-term records of browning that are directly comparable across missions. Addressing these interoperability issues is essential if EO is to capture the coupled dynamics of browning with stratification, productivity, and blooms.

Perhaps the greatest contribution of EO lies in detecting and understanding compound events. By integrating data on ice cover, surface temperature, water level, chlorophyll-a, and water colour, EO enables the identification of concurrent or sequential extremes. For example, simultaneous heatwave

and bloom detection can provide early warning of hypoxia and fish kill risk. Similarly, flood-driven browning followed by a heatwave can highlight risks of underwater dimming and productivity collapse. These compound-event capabilities are especially valuable because the impacts are non-additive and emergent, often resulting in system-wide tipping (Woolway et al. 2025). Yet achieving this requires temporally consistent, harmonised EO products so that co-occurring shifts in different variables can be reliably linked as part of a single phenological cascade.

EO is also invaluable for model integration. Data assimilation into process-based models improves hindcast validation and future projections, ensuring that models can reproduce known historic events before being applied to forecast tipping under climate change. In parallel, EO datasets can be used to train machine learning models and validate statistical approaches, helping to constrain uncertainties across modelling frameworks. Here, too, consistent multi-sensor integration is vital: models that assimilate surface temperature from one satellite record and chlorophyll-a from another require confidence that the two datasets are comparable across missions and timescales. Without this, the linkages central to combined phenology may be misrepresented.

Finally, EO supports the development of early-warning indicators. Continuous time-series of surface temperature, water colour, and bloom intensity can be analysed for rising variance, autocorrelation, or structural breaks, offering potential signals of approaching tipping points. Machine learning approaches trained on EO and in situ datasets can help detect these signals and classify precursor states. But here again, signal detection depends critically on consistent, harmonised EO records: early-warning methods that rely on subtle shifts in variance or autocorrelation are highly sensitive to artefacts introduced by sensor differences. Biases in data availability and sensitivity to observational artefacts can complicate the interpretation of these indicators when using EO data alone. To improve robustness, a model-based approach that assimilates EO observations into lake process models would allow for noise reduction, physical consistency, and uncertainty quantification before applying early-warning analyses. This integrated framework would strengthen the detection of early-warning signals and enhance confidence in interpreting potential regime shifts in lake systems. By scaling insights from local case studies to global assessments, EO contributes not only to scientific understanding but also to proactive lake management and conservation, but only if the interoperability of EO missions is addressed as a priority.

7 Surface water albedo

7.1 The variability of lake surface albedo

The Earth's radiative budget and climate are highly sensitive to modifications of the surface albedo due to land-use changes (Myhre et al. 2005; Seneviratne et al. 2018). But the albedo of lakes is still largely neglected in climate research. A recent but not overly cited (30 Scopus citations in 4.5 years) Nature Energy study has investigated climate feedback for the impoundment of hydropower reservoirs (Wohlfahrt et al. 2021). Other than that, the effects of varying lake surface albedos are largely unknown.

Wohlfahrt et al. (2021) weighted the climate warming effect of low albedo reservoirs ('albedo-climate penalty') against the climate cooling effect resulting from the saving of CO₂ emissions from fossil fuels. This effect can significantly reduce their effectiveness as a climate protection measure. They estimate that 12% of all reservoirs may not even reach the break-even after 80 years of operations, especially in arid low latitude areas with naturally high terrestrial surface albedo and accordingly the largest albedo-climate penalties. In their study, water surface albedos (0.078±0.042) were roughly half the albedos of flooded land surfaces (0.157±0.031). It must however be considered that reservoirs contribute only 8.7% to the global lake area of 0.3 M km² (Raymond et al. 2013), both of which are, at global scales, humble numbers.

Albedo variations of mountain streams were measured by (McMahon and Moore 2017). Their pyranometer measurements show how albedo varies with sun zenith angle, suspended sediment concentration, as well as the ratio of diffuse to direct irradiance and aeration and (Figure 10). Their

results show that the albedo of surface water significantly exceeds that reported in the study by Wolfahrt et al. (2021). In addition to the solar zenith angle, particle concentration is almost as decisive.

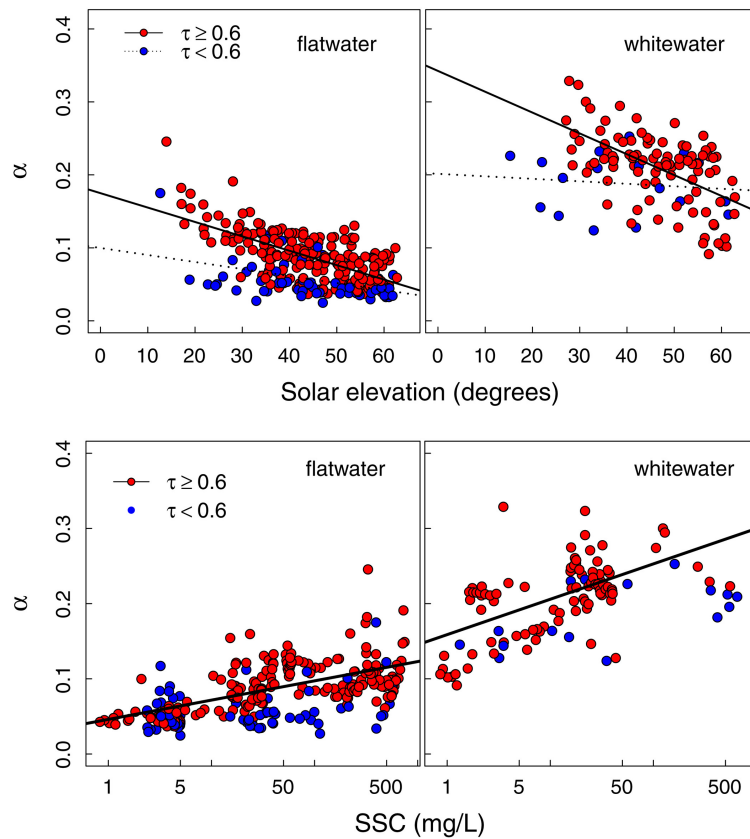


Figure 10: Mountain stream albedo variations with reference to solar elevation (top) and Suspended Sediment Concentration (SSC, bottom). τ is the atmospheric transmissivity, i.e., high τ indicate predominance of direct solar illumination. Whitewater refers to measurements over visibly aerated flow and is hence less representative for lakes than flatwater. From McMahon & Moore (2017).

Lake surface albedo in Northeast China was measured by (Du et al. 2023). Like in the results by McMahon & Moore (2017), they found albedo variations primarily with respect to the sun zenith angle, but an almost equivalent increase with particle concentrations (referred to as total suspended matter or TSM, Figure 11). Furthermore, lake surface albedo increases with wind speed, which they explain with particle resuspension effects in shallow lakes. Increasing roughness is however also known to increase water surface albedo (Mobley 1999).

The particle concentration in lakes varies by more than an order of magnitude between different lakes, and by approximately an order of magnitude seasonally. Furthermore, it can be increased or decreased by ecosystem shifts, particularly because of the increase in benthic organisms such as macrophytes or mussels. For example, (Binding et al. 2024) have observed such shifts in multi-mission remotely sensed Secchi products for the Laurentian Great Lakes.

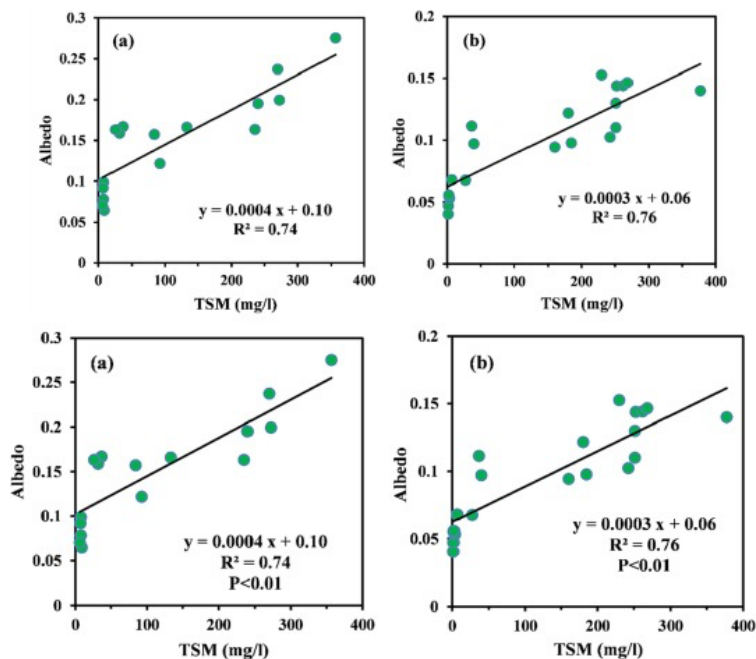


Figure 11: Relationship between lake surface albedo and total suspended matter (TSM) concentration for cases with (a) large sun zenith angles and (b) small sun zenith angles (from Du et al., 2023).

Recent work on the Tibetan Plateau has further underscored the importance of realistic lake–atmosphere coupling in climate simulations. Using the WRF model, (Qiu et al. 2025) showed that lake expansion induces a dipolar precipitation response, with decreases in the south and increases in the north of the Plateau, mediated by changes in surface heat fluxes and circulation patterns. These results illustrate how sensitive climate simulations are to the representation of lake surface processes. By analogy, neglecting realistic lake albedo — particularly in turbid systems with high backscattering — may similarly bias surface energy budgets and downstream climatic responses. Incorporating dynamic, observation-constrained albedo into lake modules of Earth system models is therefore essential for improving predictive accuracy.

7.2 Representation of water surface albedo in weather and climate models

Three weather and climate models are considered here: the Weather Research and Forecasting Model¹ (WRF), the Community Earth System Model² (CESM) and the European Centre for Medium-Range Weather Forecast’s (ECMWF) Integrated Forecasting System³ (IFS) model. They use the 1D lake models Flake⁴ (Kirillin et al. 2011) and CLM⁵ (Benjamin et al. 2022) to simulate temperature stratification, surface heat exchange and ice cover duration, and optionally also for albedo. The CLM documentation refers to (Pivovarov 1972) and Equation 1 as an albedo model, which however does not yield appropriate values for albedo a for sun zenith angles z .

¹ https://www2.mmm.ucar.edu/wrf/users/wrf_users_guide/build/html/namelist_variables.html

² <https://www.cesm.ucar.edu/models>

³ <https://www.ecmwf.int/en/forecasts/documentation-and-support/changes-ecmwf-model>

⁴ <http://www.flake.igb-berlin.de/>

⁵ https://escomp.github.io/CTSM/release-clm5.0/tech_note/Lake/CLM50_Tech_Note_Lake.html

$$a = \frac{0.5}{\cos z + 0.15} \quad \text{Eq. 1}$$

Since we cannot access the original source (Pivovarov, 1972), we instead evaluate Equation 2, which is provided by (Henderson-Sellers 1986), with reference to Pivovarov (1972) and using the sun elevation angle α^* and $a_0 = 0.04$.

$$a = \frac{a_0}{a_0 + \sin \alpha^*} \quad \text{Eq. 2}$$

In this way, we obtained values that closely resemble those referred to as the Briegleb model evaluated in (Du et al. 2023), which strongly underestimate the albedo in turbid lakes in Northeast China (Figure 10), just like all other parametric models that neglect water-leaving radiance. (Wei et al. 2023) investigates how neglecting ocean interior reflectance affects Arctic surface temperature simulations, using a model that varies albedo with sun zenith angle, chlorophyll-a concentration and wind speed. The range of albedos resulting from these parameterisations is limited to < 0.1 and they hence observe an enhanced climate warming relative to simulations neglecting the ocean's interior reflectance. Similar studies are missing for lakes, which typically have much higher water-leaving reflectance than oceans due to inorganic particle backscattering.

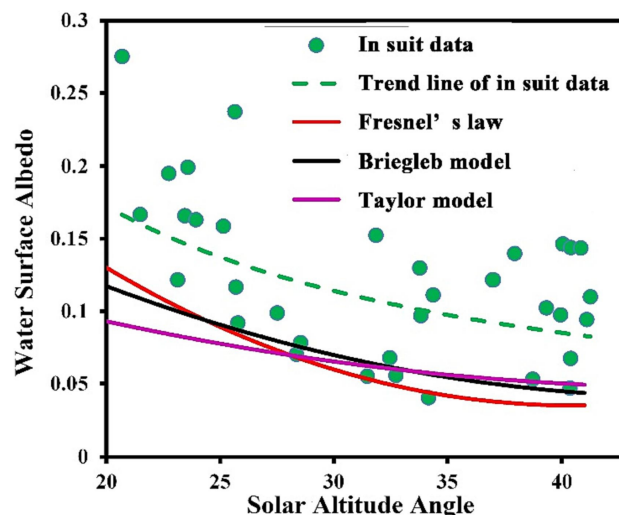


Figure 12: Comparison of measured and modelled albedos for turbid lakes in Northeast China lakes (from Du et al., 2023).

Alternatively, weather and climate models can use MODIS albedo products (Schaaf et al. 2002) or static albedo maps as input. They are not generally meant or widely used to as water surface albedo input. A rough review of MCD43A3 products shows that they also contain data on lakes. For example, in a product for Lake Huron (Figure 13), the values fluctuate quite erratically between 0.004 and 0.168 within relatively short distances. However, the water surface reflectance leads to an albedo of at least 0.02 (see, for example, the Fresnel case in Figure 10), and the turbidity in the main basin of Lake Huron is far too low to reach an albedo in the range of the lakes in northeastern China. Thus, the product is clearly not a useful approximation of the albedo of water surfaces, and it seems that parametric models such as those shown in Figure 10 are currently the best option.

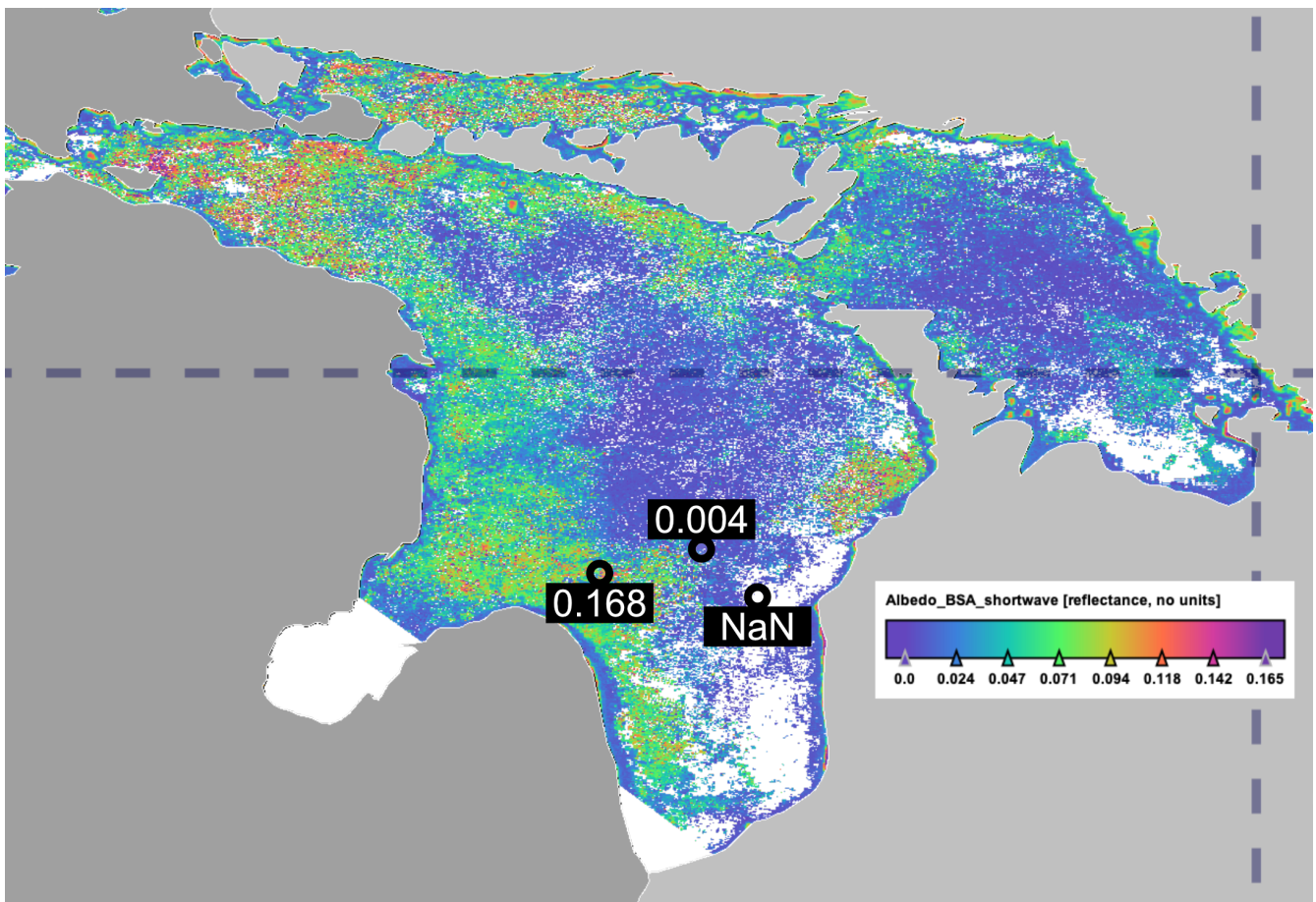


Figure 13: MODIS shortwave black sky albedo product of Lake Huron (MCD43A3.A2025210.h12v04.061) with masked land areas.

7.3 Knowledge gaps

The first question is whether the approximations used for the water surface albedo as a function of the solar zenith angle are sufficiently accurate, or rather, how much climate simulations would benefit from better input data. We were unable to find any sensitivity studies for lakes. Such studies should focus on the climate impact of lakes that are as large and murky as possible, e.g., the Caspian Sea or Lake Turkana.

A second question is to what extent changes in sea surface albedo resulting from ecosystem shifts represent feedback on the climate. For example, turbidity in the Great Lakes decreased significantly in the early 2000s, before the trend reversed again in the 2010s (Zheng and DiGiacomo 2022; Binding et al. 2024). These changes are in the range of a few turbidity units (NTU) or g/m^3 of suspended matter, so their influence is far less significant than the neglect of water-leaving radiance in the case of very turbid lakes. However, the area of the Great Lakes is so large that it still may have an effect.

7.4 Potential contribution from EO

Lake albedo can be derived directly from optical satellite data acquired under cloud-free conditions, by converting the water-leaving and air-water interface reflectance (i.e., two hemispherical-directional reflectances) into black sky albedo (i.e., bi-directional reflectance) or white sky albedo (i.e., bi-hemispherical reflectance). In such cases, the conversion could be calculated based on directional in-water and air-water interface model simulations, e.g., Hydrolight. Gap-filling during cloudy days could be accomplished using interpolated water constituent products and the albedos simulated for them.

So, if there is a need for albedo products for very large lakes, these could be developed by ESA Lakes CCI as a supplement, like the MODIS land albedo products. Deriving aquatic albedo from Earth observation data is however not a common task in lake remote sensing, so a moderate amount of development work would be required.

8 References

- Austin, J. A., and S. M. Colman. 2007. Lake Superior summer water temperatures are increasing more rapidly than regional air temperatures: A positive ice-albedo feedback. *Geophys Res Lett* **34**: L06604. doi:10.1029/2006GL029021
- Bartosiewicz, M., A. Przytulska, J. F. Lapierre, I. Laurion, M. F. Lehmann, and R. Maranger. 2019. Hot tops, cold bottoms: Synergistic climate warming and shielding effects increase carbon burial in lakes. *Limnol Oceanogr Lett* **4**: 132–144. doi:10.1002/lol2.10117
- Bastviken, D., L. J. Tranvik, J. A. Downing, P. M. Crill, and A. Enrich-Prast. 2011. Freshwater methane emissions offset the continental carbon sink. *Science* (1979) **331**: 50. doi:10.1126/science.1196808
- Basu, A., J. Culpepper, K. Blagrove, and S. Sharma. 2024. Phenological Shifts in Lake Ice Cover Across the Northern Hemisphere: A Glimpse Into the Past, Present, and the Future of Lake Ice Phenology. *Water Resour Res* **60**. doi:10.1029/2023WR036392
- Belkin, I. M., and J. E. O'Reilly. 2009. An algorithm for oceanic front detection in chlorophyll and SST satellite imagery. *Journal of Marine Systems* **78**: 319–326. doi:10.1016/j.jmarsys.2008.11.018
- Benjamin, S. G. and others. 2022. Inland lake temperature initialization via coupled cycling with atmospheric data assimilation. *Geosci Model Dev* **15**: 6659–6676. doi:10.5194/gmd-15-6659-2022
- Binding, C., M. Morison, M. Sayers, K. Bosse, X. Zhu, C. Zeng, and V. Theenathayalan. 2024. Assessing water clarity status and long-term trends in North America's largest lakes using ESA's Ocean Colour Climate Change Initiative (OC-CCI) products. *J Great Lakes Res.* doi:10.1016/j.jglr.2024.102454
- Blanchet, C. C. and others. 2022. Ecology and extent of freshwater browning - What we know and what should be studied next in the context of global change. *Science of The Total Environment* **812**: 152420. doi:10.1016/J.SCITOTENV.2021.152420
- Blanchet, F. G., K. Cazelles, and D. Gravel. 2020. Co-occurrence is not evidence of ecological interactions. *Ecol Lett* **23**: 1050–1063. doi:10.1111/ELE.13525
- Boehrer, B., and M. Schultze. 2008. Stratification of lakes. *Reviews of Geophysics* **46**: RG2005. doi:10.1029/2006RG000210
- Brezonik, P. L., L. G. Olmanson, J. C. Finlay, and M. E. Bauer. 2015. Factors affecting the measurement of CDOM by remote sensing of optically complex inland waters. *Remote Sens Environ* **157**: 199–215. doi:10.1016/J.RSE.2014.04.033
- Brothers, S., J. Köhler, K. Attermeyer, H. P. Grossart, T. Mehner, N. Meyer, K. Scharnweber, and S. Hilt. 2014. A feedback loop links brownification and anoxia in a temperate, shallow lake. *Limnol Oceanogr* **59**: 1388–1398. doi:10.4319/lo.2014.59.4.1388
- Brovkin, V. and others. 2025. Permafrost and Freshwater Systems in the Arctic as Tipping Elements of the Climate System. *Surveys in Geophysics* 2025 1–24. doi:10.1007/S10712-025-09885-9
- Calamita, E., M. Brechbühler, R. I. Woolway, C. Albergel, L. Carrea, and D. Odermatt. 2025. Satellite remote sensing reveals mixing anomalies and regime shifts in dimictic lakes. doi:UnderReview
- Calamita, E., J. J. Lever, C. Albergel, R. I. Woolway, and D. Odermatt. 2024. Detecting climate-related shifts in lakes: A review of the use of satellite Earth Observation. *Limnol Oceanogr* **69**: 723–741. doi:10.1002/lno.12498

- Calamita, E., S. Piccolroaz, B. Majone, and M. Toffolon. 2021. On the role of local depth and latitude on surface warming heterogeneity in the Laurentian Great Lakes. *Inland Waters* 1–15. doi:10.1080/20442041.2021.1873698
- Carder, K. L., R. A. Arnone, and Z. Lee. 2002. Deriving inherent optical properties from water color: a multiband quasi-analytical algorithm for optically deep waters. *Applied Optics*, Vol. 41, Issue 27, pp. 5755–5772 **41**: 5755–5772. doi:10.1364/AO.41.005755
- Carrea, L. and others. 2023. Satellite-derived multivariate world-wide lake physical variable timeseries for climate studies. *Sci Data* **10**: 30. doi:10.1038/s41597-022-01889-z
- Carrea, L. and others. 2024. ESA Lakes Climate Change Initiative (Lakes_cci): Lake products, Version 2.1. NERC EDS Centre for Environmental Data Analysis. doi:10.5285/7fc9df8070d34cacab8092e45ef276f1
- Couture, S., D. Houle, and C. Gagnon. 2012. Increases of dissolved organic carbon in temperate and boreal lakes in Quebec, Canada. *Environmental Science and Pollution Research* **19**: 361–371. doi:10.1007/S11356-011-0565-6/FIGURES/4
- Culpepper, J. and others. 2025. One-Hundred Fundamental, Open Questions to Integrate Methodological Approaches in Lake Ice Research. *Water Resour Res* **61**. doi:10.1029/2024WR039042
- Du, J., P. A. Jacinthe, K. Song, and H. Zhou. 2023. Water surface albedo and its driving factors on the turbid lakes of Northeast China. *Ecol Indic* **146**: 109905. doi:10.1016/J.ECOLIND.2023.109905
- Duarte, C. M., and Y. T. Prairie. 2005. Prevalence of Heterotrophy and Atmospheric CO₂ Emissions from Aquatic Ecosystems. *Ecosystems* 2005 8:7 **8**: 862–870. doi:10.1007/S10021-005-0177-4
- Evans, C. D., P. J. Chapman, J. M. Clark, D. T. Monteith, and M. S. Cresser. 2006. Alternative explanations for rising dissolved organic carbon export from organic soils. *Glob Chang Biol* **12**: 2044–2053. doi:10.1111/j.1365-2486.2006.01241.x
- Favot, E. J., K. M. Rühland, A. M. Desellas, R. Ingram, A. M. Paterson, and J. P. Smol. 2019. Climate variability promotes unprecedented cyanobacterial blooms in a remote, oligotrophic Ontario lake: evidence from paleolimnology. *J Paleolimnol* **62**: 31–52. doi:10.1007/S10933-019-00074-4
- Ficek, D., T. Zapadka, and J. Dera. 2011. Remote sensing reflectance of Pomeranian lakes and the Baltic. *Oceanologia* **53**: 959–970. doi:10.5697/OC.53-4.959
- Fichot, C. G., K. Matsumoto, B. Holt, M. M. Gierach, and K. S. Tokos. 2019. Assessing change in the overturning behavior of the Laurentian Great Lakes using remotely sensed lake surface water temperatures. *Remote Sens Environ* **235**: 111427. doi:10.1016/j.rse.2019.111427
- Fichot, C. G., M. Tzortziou, and A. Mannino. 2023. Remote sensing of dissolved organic carbon (DOC) stocks, fluxes and transformations along the land-ocean aquatic continuum: advances, challenges, and opportunities. *Earth Sci Rev* **242**: 104446. doi:10.1016/J.EARSCIREV.2023.104446
- Finstad, A. G., T. Andersen, S. Larsen, K. Tominaga, S. Blumentrath, H. A. De Wit, H. Tømmervik, and D. O. Hessen. 2016. From greening to browning: Catchment vegetation development and reduced S-deposition promote organic carbon load on decadal time scales in Nordic lakes. *Sci Rep* **6**: 1–8. doi:10.1038/SREP31944;SUBJMETA
- Giardino, C., M. Bresciani, D. Stroppiana, A. Oggioni, and G. Morabito. 2013. Optical remote sensing of lakes: an overview on Lake Maggiore. *J Limnol* **73**. doi:10.4081/jlimnol.2014.817
- Gilarranz, L. J., A. Narwani, D. Odermatt, R. Siber, and V. Dakos. 2022. Regime shifts, trends, and variability of lake productivity at a global scale. *Proceedings of the National Academy of Sciences* **119**: e2116413119. doi:10.1073/pnas.2116413119
- Hanson, P. C., D. L. Bade, S. R. Carpenter, and T. K. Kratz. 2003. Lake metabolism: Relationships with dissolved organic carbon and phosphorus. *Limnol Oceanogr* **48**: 1112–1119.

doi:10.4319/LO.2003.48.3.1112;REQUESTEDJOURNAL:JOURNAL:19395590;WGROU:STRIN
G:PUBLICATION

- Hébert, M.-P., B. E. Beisner, M. Rautio, and G. F. Fussmann. 2021a. Warming winters in lakes: Later ice onset promotes consumer overwintering and shapes springtime planktonic food webs. *Proceedings of the National Academy of Sciences* **118**: e2114840118. doi:10.1073/pnas.2114840118
- Hébert, M.-P., B. E. Beisner, M. Rautio, and G. F. Fussmann. 2021b. Warming winters in lakes: Later ice onset promotes consumer overwintering and shapes springtime planktonic food webs. *Proceedings of the National Academy of Sciences* **118**: e2114840118. doi:10.1073/pnas.2114840118
- Henderson-Sellers, B. 1986. Calculating the surface energy balance for lake and reservoir modeling: A review. *Reviews of Geophysics* **24**: 625. doi:10.1029/RG024i003p00625
- Hessen, D. O., T. Andersen, D. Armstrong McKay, S. Kosten, M. Meerhoff, A. Pickard, and B. M. Spears. 2024. Lake ecosystem tipping points and climate feedbacks. *Earth System Dynamics* **15**: 653–669. doi:10.5194/esd-15-653-2024
- Hipsey, M. R. and others. 2019. A General Lake Model (GLM 3.0) for linking with high-frequency sensor data from the Global Lake Ecological Observatory Network (GLEON). *Geosci Model Dev* **12**: 473–523. doi:10.5194/gmd-12-473-2019
- Imboden, D. M., and A. Wüest. 1995. Mixing Mechanisms in Lakes, p. 83–138. *In* *Physics and chemistry of lakes*. Springer.
- Jane, S. F., T. M. Detmer, S. L. Larrick, K. C. Rose, E. A. Randall, K. J. Jirka, and P. B. McIntyre. 2024. Concurrent warming and browning eliminate cold-water fish habitat in many temperate lakes. *Proc Natl Acad Sci U S A* **121**. doi:10.1073/pnas.2306906120
- Jane, S. F., J. L. Mincer, M. P. Lau, A. S. L. Lewis, J. T. Stetler, and K. C. Rose. 2023. Longer duration of seasonal stratification contributes to widespread increases in lake hypoxia and anoxia. *Glob Chang Biol* **29**: 1009–1023. doi:10.1111/gcb.16525
- Jansen, J. and others. 2022. Global increase in methane production under future warming of lake bottom waters. *Glob Chang Biol* **28**: 5427–5440. doi:10.1111/GCB.16298
- Jennings, E. and others. 2009. Impacts of Climate on the Flux of Dissolved Organic Carbon from Catchments. *The Impact of Climate Change on European Lakes* 199–220. doi:10.1007/978-90-481-2945-4_12
- Kirillin, G., J. Hochschild, D. Mironov, A. Terzhevik, S. Golosov, and G. Nützmänn. 2011. FLake-Global: Online lake model with worldwide coverage. *Environmental Modelling & Software* **26**: 683–684. doi:10.1016/J.ENVSOFT.2010.12.004
- Knoll, L. B., C. E. Williamson, R. M. Pilla, T. H. Leach, J. A. Brentrup, and T. J. Fisher. 2018. Browning-related oxygen depletion in an oligotrophic lake. *Inland Waters* **8**: 255–263. doi:10.1080/20442041.2018.1452355
- Koizumi, S., M. Hamdan, I. C. Puts, A. K. Bergström, J. Karlsson, and P. Byström. 2023. Experimental warming and browning influence autumnal pelagic and benthic invertebrate biomass and community structure. *Freshw Biol* **68**: 1224–1237. doi:10.1111/fwb.14099
- Kritzberg, E. S. and others. 2020. Browning of freshwaters: Consequences to ecosystem services, underlying drivers, and potential mitigation measures. *Ambio* **49**: 375–390. doi:10.1007/S13280-019-01227-5/FIGURES/6
- Kritzberg, E. S., W. Granéli, J. Björk, C. Brönmark, P. Hallgren, A. Nicolle, A. Persson, and L. A. Hansson. 2014. Warming and browning of lakes: consequences for pelagic carbon metabolism and sediment delivery. *Freshw Biol* **59**: 325–336. doi:10.1111/FWB.12267

- Kutser, T. and others. 2016. Remote Sensing of Black Lakes and Using 810 nm Reflectance Peak for Retrieving Water Quality Parameters of Optically Complex Waters. *Remote Sensing* 2016, Vol. 8, Page 497 **8**: 497. doi:10.3390/RS8060497
- Kutser, T., and T. Soomets. 2024. Satellite data is revealing long time changes in the world largest lakes. *Scientific Reports* 2024 14:1 **14**: 14391-. doi:10.1038/s41598-024-65250-7
- Kutser, T., L. Tranvik, and D. C. Pierson. 2009. Variations in colored dissolved organic matter between boreal lakes studied by satellite remote sensing. <https://doi.org/10.1117/1.3184437> **3**: 033538. doi:10.1117/1.3184437
- Lapierre, J. F., F. Guillemette, M. Berggren, and P. A. Del Giorgio. 2013. Increases in terrestrially derived carbon stimulate organic carbon processing and CO₂ emissions in boreal aquatic ecosystems. *Nature Communications* 2013 4:1 **4**: 2972-. doi:10.1038/ncomms3972
- Laudon, H., M. Berggren, A. Ågren, I. Buffam, K. Bishop, T. Grabs, M. Jansson, and S. Köhler. 2011. Patterns and Dynamics of Dissolved Organic Carbon (DOC) in Boreal Streams: The Role of Processes, Connectivity, and Scaling. *Ecosystems* **14**: 880–893. doi:10.1007/S10021-011-9452-8
- Lever, J. J. 2025. Tracking lake phytoplankton blooms: a global remote sensing approach.
- Lewis, W. M. 1983. A Revised Classification of Lakes Based on Mixing. *Canadian Journal of Fisheries and Aquatic Sciences* **40**: 1779–1787. doi:10.1139/f83-207
- Li, J., Q. Yu, Y. Q. Tian, B. L. Becker, P. Siqueira, and N. Torbick. 2018. Spatio-temporal variations of CDOM in shallow inland waters from a semi-analytical inversion of Landsat-8. *Remote Sens Environ* **218**: 189–200. doi:10.1016/J.RSE.2018.09.014
- Liu, G. and others. 2021. Remote sensing of CDOM and DOC in alpine lakes across the Qinghai-Tibet Plateau using Sentinel-2A imagery data. *J Environ Manage* **286**: 112231. doi:10.1016/J.JENVMAN.2021.112231
- Livingstone, D. M. 2003. Impact of Secular Climate Change on the Thermal Structure of a Large Temperate Central European Lake. *Clim Change* **57**: 205–225. doi:10.1023/A:1022119503144
- Loriani, S. and others. 2025. Monitoring the Multiple Stages of Climate Tipping Systems from Space: Do the GCOS Essential Climate Variables Meet the Needs? *Surv Geophys*. doi:10.1007/s10712-024-09866-4
- Ma, J. and others. 2022. Thirty-Four-Year Record (1987–2021) of the Spatiotemporal Dynamics of Algal Blooms in Lake Dianchi from Multi-Source Remote Sensing Insights. *Remote Sens (Basel)* **14**: 4000. doi:10.3390/RS14164000/S1
- Mannino, A., M. G. Novak, S. B. Hooker, K. Hyde, and D. Aurin. 2014. Algorithm development and validation of CDOM properties for estuarine and continental shelf waters along the northeastern U.S. coast. *Remote Sens Environ* **152**: 576–602. doi:10.1016/J.RSE.2014.06.027
- Mannino, A., M. E. Russ, and S. B. Hooker. 2008. Algorithm development and validation for satellite-derived distributions of DOC and CDOM in the U.S. Middle Atlantic Bight. *J Geophys Res Oceans* **113**: 7051. doi:10.1029/2007JC004493;PAGE:STRING:ARTICLE/CHAPTER
- Massicotte, P., E. Asmala, C. Stedmon, and S. Markager. 2017. Global distribution of dissolved organic matter along the aquatic continuum: Across rivers, lakes and oceans. *Science of The Total Environment* **609**: 180–191. doi:10.1016/J.SCITOTENV.2017.07.076
- McMahon, A., and R. D. Moore. 2017. Influence of turbidity and aeration on the albedo of mountain streams. *Hydrol Process* **31**: 4477–4491. doi:10.1002/HYP.11370
- Meingast, K. M., E. S. Kane, A. A. Coble, A. M. Marcarelli, and D. Toczydlowski. 2020. Climate, snowmelt dynamics and atmospheric deposition interact to control dissolved organic carbon export from a northern forest stream over 26 years. *Environmental Research Letters* **15**: 104034. doi:10.1088/1748-9326/AB9C4E

- Mesman, J. P., J. A. A. Stelzer, V. Dakos, S. Goyette, I. D. Jones, J. Kasparian, D. F. McGinnis, and B. W. Ibelings. 2021. The role of internal feedbacks in shifting deep lake mixing regimes under a warming climate. *Freshw Biol* **66**: 1021–1035. doi:10.1111/fwb.13704
- Meyer-Jacob, C., N. Michelutti, A. M. Paterson, B. F. Cumming, W. Keller, and J. P. Smol. 2019. The browning and re-browning of lakes: Divergent lake-water organic carbon trends linked to acid deposition and climate change. *Sci Rep* **9**: 1–10. doi:10.1038/S41598-019-52912-0;TECHMETA
- Milkoreit, M. and others. 2018a. Defining tipping points for social-ecological systems scholarship—an interdisciplinary literature review. *Environmental Research Letters* **13**: 033005. doi:10.1088/1748-9326/aaaa75
- Milkoreit, M. and others. 2018b. Defining tipping points for social-ecological systems scholarship—an interdisciplinary literature review. *Environmental Research Letters* **13**: 033005. doi:10.1088/1748-9326/aaaa75
- Minor, E. C., and A. R. Oyler. 2023. Dissolved organic matter in large lakes: a key but understudied component of the carbon cycle. *Biogeochemistry* **164**: 295–318. doi:10.1007/S10533-020-00733-Z
- Mobley, C. D. 1999. Estimation of the remote-sensing reflectance from above-surface measurements. *Applied Optics*, Vol. 38, Issue 36, pp. 7442–7455 **38**: 7442–7455. doi:10.1364/AO.38.007442
- Monteith, D. T. and others. 2007. Dissolved organic carbon trends resulting from changes in atmospheric deposition chemistry. *Nature* **450**: 537–540. doi:10.1038/nature06316
- Myhre, G., M. M. Kvalevåg, and C. B. Schaaf. 2005. Radiative forcing due to anthropogenic vegetation change based on MODIS surface albedo data. *Geophys Res Lett* **32**: 1–4. doi:10.1029/2005GL024004
- Olmanson, L. G., B. P. Page, J. C. Finlay, P. L. Brezonik, M. E. Bauer, C. G. Griffin, and R. M. Hozalski. 2020. Regional measurements and spatial/temporal analysis of CDOM in 10,000+ optically variable Minnesota lakes using Landsat 8 imagery. *Science of The Total Environment* **724**: 138141. doi:10.1016/J.SCITOTENV.2020.138141
- Pahlevan, N. and others. 2022. Simultaneous retrieval of selected optical water quality indicators from Landsat-8, Sentinel-2, and Sentinel-3. *Remote Sens Environ* **270**: 112860. doi:10.1016/J.RSE.2021.112860
- Palmer, S. C. J., D. Odermatt, P. D. Hunter, C. Brockmann, M. Présing, H. Balzter, and V. R. Tóth. 2015. Satellite remote sensing of phytoplankton phenology in Lake Balaton using 10 years of MERIS observations. *Remote Sens Environ* **158**: 441–452. doi:10.1016/J.RSE.2014.11.021
- Piccolroaz, S. and others. 2024. Lake Water Temperature Modeling in an Era of Climate Change: Data Sources, Models, and Future Prospects. *Reviews of Geophysics* **62**. doi:10.1029/2023RG000816
- Pick, F. R. 2016. Blooming algae: a Canadian perspective on the rise of toxic cyanobacteria. <https://doi.org/10.1139/cjfas-2015-0470> **73**: 1149–1158. doi:10.1139/CJFAS-2015-0470
- Pickens, A. H., M. C. Hansen, S. V. Stehman, A. Tyukavina, P. Potapov, V. Zalles, and J. Higgins. 2022. Global seasonal dynamics of inland open water and ice. *Remote Sens Environ* **272**: 112963. doi:10.1016/J.RSE.2022.112963
- Pivovarov, A. A. V. E. G. P. 1972. Thermal conditions in freezing lakes and rivers. (No Title).
- Politi, E., S. MacCallum, M. E. J. Cutler, C. J. Merchant, J. S. Rowan, and T. P. Dawson. 2016. Selection of a network of large lakes and reservoirs suitable for global environmental change analysis using Earth Observation. *Int J Remote Sens* **37**: 3042–3060. doi:10.1080/01431161.2016.1192702
- Prairie, Y. T., D. F. Bird, and J. J. Cole. 2002. The summer metabolic balance in the epilimnion of southeastern Quebec lakes. *Limnol Oceanogr* **47**: 316–321. doi:10.4319/LO.2002.47.1.0316;PAGE:STRING:ARTICLE/CHAPTER

- Qiu, Y., J. Chen, D. Chen, R. I. Woolway, H. Luo, and L. Xiong. 2025. Dipolar response of precipitation to lake expansion on the Tibetan Plateau. *J Hydrol (Amst)* **660**: 133532. doi:10.1016/J.JHYDROL.2025.133532
- Raymond, P. A. and others. 2013. Global carbon dioxide emissions from inland waters. *Nature* **503**: 355–359. doi:10.1038/nature12760
- Read, J. S., and K. C. Rose. 2013. Physical responses of small temperate lakes to variation in dissolved organic carbon concentrations. *Limnol Oceanogr* **58**: 921–931. doi:10.4319/LO.2013.58.3.0921
- Chen, J., W. Zhu, Y. Q. Tian, Q. Yu, Y. Zheng, and L. Huang. 2017. Remote estimation of colored dissolved organic matter and chlorophyll-a in Lake Huron using Sentinel-2 measurements. *J Appl Remote Sens* **11**: 1. doi:10.1117/1.JRS.11.036007
- Richardson, D. C., A. Filazzola, R. I. Woolway, M. A. Imrit, D. Bouffard, G. A. Weyhenmeyer, J. Magnuson, and S. Sharma. 2024. Nonlinear responses in interannual variability of lake ice to climate change. *Limnol Oceanogr* **69**: 789–801. doi:10.1002/lno.12527
- Rodríguez-Cardona, B. M., D. Houle, S. Couture, J. F. Lapierre, and P. A. del Giorgio. 2023. Long-term trends in carbon and color signal uneven browning and terrestrialization of northern lakes. *Communications Earth & Environment* 2023 4:1 **4**: 338-. doi:10.1038/s43247-023-00999-9
- Saloranta, T. M., and T. Andersen. 2007. MyLake—A multi-year lake simulation model code suitable for uncertainty and sensitivity analysis simulations. *Ecol Modell* **207**: 45–60. doi:10.1016/j.ecolmodel.2007.03.018
- Schaaf, C. B. and others. 2002. First operational BRDF, albedo nadir reflectance products from MODIS. *Remote Sens Environ* **83**: 135–148. doi:10.1016/S0034-4257(02)00091-3
- Scheffer, M. and others. 2009a. Early-warning signals for critical transitions. *Nature* **461**: 53–59. doi:10.1038/nature08227
- Scheffer, M. and others. 2009b. Early-warning signals for critical transitions. *Nature* **461**: 53–59. doi:10.1038/nature08227
- Scheffer, M., S. Carpenter, J. A. Foley, C. Folke, and B. Walker. 2001a. Catastrophic shifts in ecosystems. *Nature* **413**: 591–596. doi:10.1038/35098000
- Scheffer, M., D. Straile, E. H. van Nes, and H. Hosper. 2001b. Climatic warming causes regime shifts in lake food webs. *Limnol Oceanogr* **46**: 1780–1783. doi:10.4319/lo.2001.46.7.1780
- Schmid, M., and J. Read. 2022. Heat Budget of Lakes, p. 467–473. *In Encyclopedia of Inland Waters, Second Edition*. Elsevier.
- Seekell, D. A., J. F. Lapierre, J. Ask, A. K. Bergstrom, A. Deininger, P. Rodriguez, and J. Karlsson. 2015. The influence of dissolved organic carbon on primary production in northern lakes. *Limnol Oceanogr* **60**: 1276–1285. doi:10.1002/LNO.10096
- Seneviratne, S. I. and others. 2018. Land radiative management as contributor to regional-scale climate adaptation and mitigation. *Nat Geosci* **11**: 88–96. doi:10.1038/s41561-017-0057-5
- Sharma, S. and others. 2019a. 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
- Sharma, S. and others. 2019b. 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;TECHMETA
- Sharma, S. and others. 2020. Integrating Perspectives to Understand Lake Ice Dynamics in a Changing World. *J Geophys Res Biogeosci* **125**. doi:10.1029/2020JG005799
- Shatwell, T., W. Thiery, and G. Kirillin. 2019. Future projections of temperature and mixing regime of European temperate lakes. *Hydrol Earth Syst Sci* **23**: 1533–1551. doi:10.5194/hess-23-1533-2019

- Sobek, S., G. Algesten, A. K. Bergström, M. Jansson, and L. J. Tranvik. 2003. The catchment and climate regulation of pCO₂ in boreal lakes. *Glob Chang Biol* **9**: 630–641. doi:10.1046/J.1365-2486.2003.00619.X;WEBSITE:WEBSITE:PERICLES;REQUESTEDJOURNAL:JOURNAL:13652486;SUBPAGE:STRING:ACCESS
- Sobek, S., L. J. Tranvik, and J. J. Cole. 2005. Temperature independence of carbon dioxide supersaturation in global lakes. *Global Biogeochem Cycles* **19**: 1–10. doi:10.1029/2004GB002264
- Solomon, C. T. and others. 2015. Ecosystem Consequences of Changing Inputs of Terrestrial Dissolved Organic Matter to Lakes: Current Knowledge and Future Challenges. *Ecosystems* **18**: 376–389. doi:10.1007/S10021-015-9848-Y/FIGURES/6
- Stefanidis, K., G. Varlas, G. Papaioannou, A. Papadopoulos, and E. Dimitriou. 2022. Trends of lake temperature, mixing depth and ice cover thickness of European lakes during the last four decades. *Science of the Total Environment* **830**. doi:10.1016/j.scitotenv.2022.154709
- Stoddard, J. L. and others. 1999. Regional trends in aquatic recovery from acidification in North America and Europe. *Nature* **401**: 575–578. doi:10.1038/44114
- Strock, K. E., J. E. Saros, S. J. Nelson, S. D. Birkel, J. S. Kahl, and W. H. McDowell. 2016. Extreme weather years drive episodic changes in lake chemistry: implications for recovery from sulfate deposition and long-term trends in dissolved organic carbon. *Biogeochemistry* **127**: 353–365. doi:10.1007/S10533-016-0185-9
- Sun, J. and others. 2018a. Linkages of the dynamics of glaciers and lakes with the climate elements over the Tibetan Plateau. *Earth Sci Rev* **185**: 308–324. doi:10.1016/j.earscirev.2018.06.012
- Sun, Q., C. Miao, Q. Duan, H. Ashouri, S. Sorooshian, and K.-L. L. Hsu. 2018b. A Review of Global Precipitation Data Sets: Data Sources, Estimation, and Intercomparisons. *Reviews of Geophysics* **56**: 79–107. doi:10.1002/2017RG000574
- Tanentzap, A. J., N. D. Yan, B. Keller, R. Girard, J. Heneberry, J. M. Gunn, D. P. Hamilton, and P. A. Taylor. 2008. Cooling lakes while the world warms: Effects of forest regrowth and increased dissolved organic matter on the thermal regime of a temperate, urban lake. *Limnol Oceanogr* **53**: 404–410. doi:10.4319/lo.2008.53.1.0404
- Till, A., A. L. Rypel, A. Bray, and S. B. Fey. 2019. Fish die-offs are concurrent with thermal extremes in north temperate lakes. *Nat Clim Chang* **9**: 637–641. doi:10.1038/s41558-019-0520-y
- Toffolon, M., S. Piccolroaz, and E. Calamita. 2020. On the use of averaged indicators to assess lakes' thermal response to changes in climatic conditions. *Environmental Research Letters* **15**: 034060. doi:10.1088/1748-9326/ab763e
- Toming, K., J. Kotta, E. Uuemaa, S. Sobek, T. Kutser, and L. J. Tranvik. 2020. Predicting lake dissolved organic carbon at a global scale. *Sci Rep* **10**: 8471. doi:10.1038/s41598-020-65010-3
- Toming, K., T. Kutser, A. Laas, M. Sepp, B. Paavel, and T. Nõges. 2016. First Experiences in Mapping Lake Water Quality Parameters with Sentinel-2 MSI Imagery. *Remote Sensing 2016*, Vol. 8, Page 640 **8**: 640. doi:10.3390/RS8080640
- Toussaint, F., A. Alonso, and M. Vanclooster. 2025. Leveraging 20 Years of Remote Sensing to Characterize Surface Phytoplankton Seasonality and Long-Term Trends in Lake Tanganyika. *EGU sphere* 1–24. doi:10.5194/EGUSPHERE-2025-1326
- Tranvik, L. J. and others. 2009. Lakes and reservoirs as regulators of carbon cycling and climate. *Limnol Oceanogr* **54**: 2298–2314. doi:10.4319/lo.2009.54.6_part_2.2298
- Ullman, D., J. Brown, P. Cornillon, and T. Mavor. 1998. Surface temperature fronts in the Great Lakes. *J Great Lakes Res* **24**: 753–775. doi:10.1016/S0380-1330(98)70860-3

- Urrutia-Cordero, P., M. K. Ekvall, J. Ratcovich, M. Soares, S. Wilken, H. Zhang, and L. A. Hansson. 2017. Phytoplankton diversity loss along a gradient of future warming and brownification in freshwater mesocosms. *Freshw Biol* **62**: 1869–1878. doi:10.1111/FWB.13027
- Vagle, S., and E. Carmack. 2023. Annual patterns of stratification, mixing and ventilation in long, deep, seasonally ice-covered François lake, British Columbia, Canada. *Front Earth Sci (Lausanne)* **11**. doi:10.3389/feart.2023.1090124
- Vanderkelen, I. and others. 2020. Global Heat Uptake by Inland Waters. *Geophys Res Lett* **47**. doi:10.1029/2020GL087867
- Verpoorter, C., T. Kutser, D. A. Seekell, and L. J. Tranvik. 2014. A global inventory of lakes based on high-resolution satellite imagery. *Geophys Res Lett* **41**: 6396–6402. doi:10.1002/2014GL060641
- Wagner, C., and R. Adrian. 2009a. Exploring lake ecosystems: hierarchy responses to long-term change? *Glob Chang Biol* **15**: 1104–1115. doi:10.1111/j.1365-2486.2008.01833.x
- Wagner, C., and R. Adrian. 2009b. Exploring lake ecosystems: hierarchy responses to long-term change? *Glob Chang Biol* **15**: 1104–1115. doi:10.1111/j.1365-2486.2008.01833.x
- Wei, J., T. Ren, P. Yang, S. F. DiMarco, and X. Huang. 2023. Sensitivity of Arctic Surface Temperature to Including a Comprehensive Ocean Interior Reflectance to the Ocean Surface Albedo Within the Fully Coupled CESM2. *J Adv Model Earth Syst* **15**: e2023MS003702. doi:10.1029/2023MS003702
- Wen, H. and others. 2020. Temperature controls production but hydrology regulates export of dissolved organic carbon at the catchment scale. *Hydrol Earth Syst Sci* **24**: 945–966. doi:10.5194/HESS-24-945-2020
- Williamson, C. E., J. A. Brentrup, J. Zhang, W. H. Renwick, B. R. Hargreaves, L. B. Knoll, E. P. Overholt, and K. C. Rose. 2014. Lakes as sensors in the landscape: Optical metrics as scalable sentinel responses to climate change. *Limnol Oceanogr* **59**: 840–850. doi:10.4319/lo.2014.59.3.0840
- Williamson, C. E., E. P. Overholt, R. M. Pilla, T. H. Leach, J. A. Brentrup, L. B. Knoll, E. M. Mette, and R. E. Moeller. 2015a. Ecological consequences of long-term browning in lakes. *Sci Rep* **5**: 1–10. doi:10.1038/SREP18666;SUBJMETA
- Williamson, C. E., E. P. Overholt, R. M. Pilla, T. H. Leach, J. A. Brentrup, L. B. Knoll, E. M. Mette, and R. E. Moeller. 2015b. Ecological consequences of long-term browning in lakes. *Sci Rep* **5**. doi:10.1038/srep18666
- Winder, M., and D. E. Schindler. 2004. Climatic effects on the phenology of lake processes. *Glob Chang Biol* **10**: 1844–1856. doi:10.1111/J.1365-2486.2004.00849.X
- WMO. 2022. The 2022 GCOS ECVs Requirements (GCOS 245).
- Wohlfahrt, G., E. Tomelleri, and A. Hammerle. 2021. The albedo–climate penalty of hydropower reservoirs. *Nat Energy* **6**: 372–377. doi:10.1038/s41560-021-00784-y
- Woolway, R. I. and others. 2021a. Phenological shifts in lake stratification under climate change. *Nat Commun* **12**: 2318. doi:10.1038/s41467-021-22657-4
- Woolway, R. I. and others. 2025. Extreme and compound events in lakes. *Nat Rev Earth Environ* **6**: 593–611. doi:10.1038/S43017-025-00710-W;SUBJMETA
- Woolway, R. I., E. J. Anderson, and C. Albergel. 2021b. Rapidly expanding lake heatwaves under climate change. *Environmental Research Letters* **16**: 094013. doi:10.1088/1748-9326/ac1a3a
- Woolway, R. I., E. Jennings, and L. Carrea. 2020a. Impact of the 2018 European heatwave on lake surface water temperature. *Inland Waters* 1–11. doi:10.1080/20442041.2020.1712180
- Woolway, R. I., E. Jennings, T. Shatwell, M. Golub, D. C. Pierson, and S. C. Maberly. 2021c. Lake heatwaves under climate change. *Nature* **589**: 402–407. doi:10.1038/s41586-020-03119-1

- Woolway, R. I., B. M. Kraemer, J. D. Lenters, C. J. Merchant, C. M. O'Reilly, and S. Sharma. 2020b. Global lake responses to climate change. *Nat Rev Earth Environ* **1**: 388–403. doi:10.1038/s43017-020-0067-5
- Woolway, R. I., B. M. Kraemer, J. D. Lenters, C. J. Merchant, C. M. O'Reilly, and S. Sharma. 2020c. Global lake responses to climate change. *Nat Rev Earth Environ* **1**: 388–403. doi:10.1038/s43017-020-0067-5
- Woolway, R. I., B. M. Kraemer, J. Zscheischler, and C. Albergel. 2021d. Compound hot temperature and high chlorophyll extreme events in global lakes. *Environmental Research Letters* **16**: 124066. doi:10.1088/1748-9326/ac3d5a
- Woolway, R. I., and C. J. Merchant. 2017. Amplified surface temperature response of cold, deep lakes to inter-annual air temperature variability. *Sci Rep* **7**: 4130. doi:10.1038/s41598-017-04058-0
- Woolway, R. I., and C. J. Merchant. 2019. Worldwide alteration of lake mixing regimes in response to climate change. *Nat Geosci* **12**: 271–276. doi:10.1038/s41561-019-0322-x
- Woolway, R. I., G. A. Weyhenmeyer, M. Schmid, M. T. Dokulil, E. de Eyto, S. C. Maberly, L. May, and C. J. Merchant. 2019. Substantial increase in minimum lake surface temperatures under climate change. *Clim Change* 1–14. doi:10.1007/s10584-019-02465-y
- Yi, C. and others. 2025. Principles for guiding future research on resilience and tipping points. *Environmental Research Letters* **20**. doi:10.1088/1748-9326/adb7f3
- Zhang, G. and others. 2023. Underestimated mass loss from lake-terminating glaciers in the greater Himalaya. *Nat Geosci* **16**: 333–338. doi:10.1038/s41561-023-01150-1
- Zhang, Y., K. Shi, R. I. Woolway, X. Wang, and Y. Zhang. 2025. Climate warming and heatwaves accelerate global lake deoxygenation. *Sci Adv* **11**: 5369. doi:10.1126/SCIADV.ADT5369
- Zheng, G., and P. M. DiGiacomo. 2022. A simple water clarity-turbidity index for the Great Lakes. *J Great Lakes Res* **48**: 686–694. doi:10.1016/J.JGLR.2022.03.005
- Zhu, W., and Q. Yu. 2013. Inversion of chromophoric dissolved organic matter from EO-1 hyperion imagery for turbid estuarine and coastal waters. *IEEE Transactions on Geoscience and Remote Sensing* **51**: 3286–3298. doi:10.1109/TGRS.2012.2224117
- Zhu, W., Q. Yu, Y. Q. Tian, B. L. Becker, T. Zheng, and H. J. Carrick. 2014. An assessment of remote sensing algorithms for colored dissolved organic matter in complex freshwater environments. *Remote Sens Environ* **140**: 766–778. doi:10.1016/J.RSE.2013.10.015