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Review article

Monitoring earth's glacial lakes from space with machine learning

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ABSTRACT

The rapid worldwide formation and expansion of glacial lakes has increased the likelihood of glacial lake outburst floods, threatening lives and infrastructure, particularly in vulnerable mountain communities. Given the rapid increase in the popularity of artificial intelligence methods for remote sensing of glacial lakes, a comprehensive review is essential. We survey a decade (2015–2024) of research on glacial lake monitoring from space, with a focus on classical machine learning and deep learning approaches. We identify key trends, research gaps, and best practices for future studies. Most studies rely on optical imagery, especially Landsat-8 and Sentinel-2, while Sentinel-1 serves as a complementary radar source. However, monitoring glacial lakes in mountainous regions remains a challenge on cloudy days due to the limitations of radar and the unusability of optical data. Deep learning, particularly U-Net and DeepLab derivatives, dominates learning-based glacial lake studies but remains computationally demanding. Critical challenges involve balancing performance gains against trade-offs in data availability, computational cost, and model transferability. Geographic and methodological gaps, especially in regions experiencing rapid lake growth, underscore the need for broader spatial coverage and improved spatiotemporal model generalization. Moreover, transitioning from a focus on static seasonal mapping to frequent multi-temporal monitoring is beneficial for understanding glacial lake evolution and outburst flood hazards. Adapting emerging deep learning architectures to integrate multispectral, hyperspectral, and radar data could enhance glacial lake detection capabilities. Furthermore, thorough inter-method comparisons, benchmarking with rigorous evaluation metrics, and open-sourcing datasets and code would facilitate robust, large-scale glacial lake monitoring efforts.

1. Introduction

Approximately 1.74% of Earth's water is stored in glaciers, ice caps, and permanent snow cover, accounting for about 68.7% of global freshwater (Shiklomanov, 1993). Glacial lakes are water bodies formed by the accumulation of meltwater in depressions created by glacier retreat, including those dammed by ice, moraines, or other glacially deposited materials (Costa and Schuster, 1987). Climate change-driven glacier mass loss is accelerating the formation and expansion of glacial lakes (NASA Decadal Survey, 2007; King et al., 2019; Shugar et al., 2020).

Globally, more than 110,000 glacial lakes have been documented, with a total mapped area of approximately 15,000 km^2, based on studies conducted between 2006 and 2020 (Zhang et al., 2024). Glacial lakes are integral to regional freshwater systems, storing meltwater and influencing hydrological cycles (Mingwei et al., 2025). At the same time, due to their dynamic nature, some of these lakes are sources of Glacial Lake Outburst Flood (GLOF)s, endangering lives and critical infrastructure worldwide (Emmer et al., 2022; Taylor et al., 2023). Over 3000 GLOFs were recorded from the year 850 to 2022, while the total glacial lake area increased by approximately 22% per decade between 1990 and 2020 (Zhang et al., 2024).

Multi-temporal monitoring of glacial lakes is beneficial for assessing GLOF hazards, developing early warning systems for the protection of downstream communities, and improving water resource management (Rinzin et al., 2023; Ahmed, 2024; Emmer, 2024). However, implementing effective and scalable monitoring strategies remains challenging due to the inherent variability in glacial lake characteristics, including differences in size, shape, depth, and turbidity. Many of these lakes are small (area <0.1 km^2) and remain frozen for several months, exhibiting distinctive geomorphologic traits (Carrivick and

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Tweed, 2013; Costa and Schuster, 1987; Clague and Evans, 2000). Beyond these physical variations, the diversity of lake formation environments makes systematic observation difficult. These include proglacial (rock-dammed, moraine-dammed, ice-dammed), ice-marginal (glacier-blocked), supraglacial, and subglacial settings (Costa and Schuster, 1987).

In situ measurements of glacial lakes capture a wide range of parameters, including lake water level, area changes, bathymetry, temperature, precipitation, and ice cover, among others (Fujita et al., 2009; Tedesco and Steiner, 2011; Sharma et al., 2018). These measurements are often sparse, as field campaigns to glacial lakes are challenging due to their remote, high-altitude, or high-latitude locations adjacent to glaciers (Treichler et al., 2019). Consequently, satellite and airborne observations often serve as complementary, and in some cases, primary methods for large-scale and continuous monitoring. These remote sensing techniques specifically focus on the geographic extent of surface lakes. However, they provide critical insights where direct measurements are limited (Huang et al., 2018).

Several approaches exist for mapping glacial lake extent using remote sensing. An example is Geographic Information System (GIS)-assisted manual lake boundary delineation and inventory creation methods. These methods leverage human expertise to interpret data and define boundaries from satellite observations (Ukita et al., 2011; Raj and Kumar, 2016; Petrov et al., 2017; Senese et al., 2018, etc.). However, such manual approaches are feasible only on a small scale and/or for a few time steps due to their labor intensive nature. In contrast, automated remote sensing methods offer greater scalability and enable the fusion of information from multiple data sources—including optical and radar imagery.

There has been a notable rise in the popularity of classical ML and DL methods for land cover classification applications over the past decade. These learning-based methods, in conjunction with remote sensing, have achieved significant breakthroughs across various subfields of geoscience (Karpatne et al., 2019; Camps-Valls et al., 2021; Ge et al., 2022). Such advancements also span hydrosphere (Sit et al., 2020) and cryosphere (Liu, 2021) monitoring.

Unlike traditional non-ML approaches, data-driven ML algorithms effectively learn intricate patterns from representative remote sensing datasets, enabling more accurate and efficient analysis (Maxwell et al., 2018). DL methods, while demanding in terms of training data requirements, automatically extract features – such as texture and spatial relationships – directly from data. They learn hierarchical representations and outperform classical ML methods in many fields of Earth sciences (Tuia et al., 2024; Taylor et al., 2021). However, these data-driven methods also have limitations. These include high data and computational demands, large model sizes that hinder deployment, challenges in geographical transferability, and debatable interpretability and explainability.

The potential value and widespread adoption of diverse learning-based methods underscore the need for a detailed review. A comprehensive evaluation of existing approaches, along with a synthesis of their strengths and limitations, the establishment of best practices, and the identification of key research gaps, is essential.

Though numerous research papers in the past decade have applied ML/DL to map and monitor glacial lakes, a dedicated review remains absent. Some surveys exist on related topics—such as ML/DL for water body detection (Gautam and Singhai, 2024) and lake-water level fluctuation forecasting (Sannasi Chakravarthy et al., 2022). However, none specifically focus on remote sensing of glacial lakes. Similarly, reviews on non-ML approaches – such as bibliometric analysis of glacial lake identification (Zhengquan et al., 2023), frozen lake extraction from optical data (Jawak et al., 2015), and remote sensing applications in the mountain cryosphere (Taylor et al., 2021) – offer valuable insights. However, they do not address Artificial Intelligence (AI)-driven methodologies. The paper is structured as follows: Section 2 discusses spatiotemporal aspects in learning-based glacial lake studies, while Section 3 provides an overview of the remote sensing data used. Section 4 explores ML/DL methodologies for studying proglacial, ice-marginal, and supraglacial lakes from space, followed by Section 5, which presents key challenges and limitations. Finally, Section 6 concludes with recommendations for future research.

2. Learning-based glacial lake studies: A spatio-temporal perspective

2.1. Beyond seasonal mapping: Toward multi-temporal monitoring

The first step in a glacial lake study is mapping. This involves creating an inventory or map of lakes in a study region using an underlying ML/DL model, typically based on satellite data from a single point in time. Mapping is essential for providing a snapshot of glacial lake extents and serving as a proof-of-concept. However, it alone cannot capture seasonal fluctuations, indicate long-term trends, or assess GLOF hazard potential.

The next critical step is monitoring, which builds on repeated mapping to systematically track glacial lake evolution over time. Learning-based studies such as Banerjee and Bhuiyan (2023), Lutz et al. (2023), and Sharma and Prakash (2023), among others, have reported monitoring efforts that extend beyond one-time mapping.

However, most studies (e.g., He et al., 2021; Wang et al., 2021) focus solely on mapping, prioritizing static lake characterization over understanding temporal dynamics. Effective monitoring requires repeated observations while balancing trade-offs between update frequency and various challenges. These challenges include data gaps due to cloud cover and inconsistent data acquisition, seasonal variability, and increased computational demands. A key constraint is the limited availability of suitable multi-temporal satellite imagery. This is especially challenging in high-mountain regions where frequent cloud cover and the lack of usable optical images (in winter) severely restrict observation windows.

Notably, repeated mapping – conducted as frequently as observation conditions allow – differs from multi-temporal monitoring. The latter involves a systematic analysis of temporal patterns, often designed to capture intra-annual variations and seasonal dynamics. To ensure the accuracy and reliability of new glacial lake extent products derived from learning-based algorithms, rigorous evaluation of multi-temporal monitoring outcomes is recommended before operational deployment.

Environmental factors such as cloud cover, haze, ice and snow cover, fog, evaporation, and surface reflectance – also referred to as sun glint or sun glitter – vary significantly over time in glaciated regions. These variations pose challenges for consistent glacial lake monitoring across all seasons (Mölg and Hardy, 2004; Hock, 2005). Frozen lakes, particularly supraglacial lakes or those in direct contact with glaciers or covered by snow, are difficult to distinguish spectrally from surrounding ice in optical satellite imagery. In some cases, spectral similarity makes detection nearly impossible during colder months. ML/DL methods can partially overcome this by learning spatial and contextual patterns beyond raw spectral values. Convolutional Neural Network (CNN)s extract multi-scale features such as texture, edges, and shape, while attention-based models use broader spatial context to improve classification. These approaches are effective when frozen lakes have distinct morphological boundaries. However, when both spectral and spatial cues are weak – such as under uniform snow cover – performance remains limited, regardless of model complexity.

Seasonal surface variations also affect radar-based glacial lake detection. Flat water surfaces typically exhibit low backscatter (Bauer-Marschallinger et al., 2021). Wind or thin floating ice can roughen water surfaces, increasing backscatter (Freilich and Vanhoff, 2003; Shaposhnikova et al., 2023). Snow has higher backscatter due to its heterogeneous structure (Rott, 1984). Ideally, the dataset used to train an ML/DL model should be representative of these variations to ensure robust detection across diverse environmental conditions.

Table 1
Examples of learning-based glacial lake studies conducted during specific seasons with favorable observation conditions.

Publication	Season	Primary study site
Dirscherl et al. (2020)	January–February	Antarctica
Dirscherl et al. (2021)	December–February	Antarctica
Yuan et al. (2020)	May–September	Southwest Greenland
Qayyum et al. (2020)	May–November	Hind Kush Karakoram Himalaya
Wang et al. (2021)	September–November	Himalayas
Xu et al. (2023)	Summer	Eastern Himalaya
Zhao et al. (2023)	July–November	High Mountain Asia
Tang et al. (2024)	June–November	Third Pole Region

To minimize the impact of seasonal challenges, learning-based glacial lake studies often target months with optimal data quality. For example, Wu et al. (2020) avoided July to September due to frequent cloud cover (southeastern Tibet), which hinders optical remote sensing. They also excluded January, when frozen conditions and lake shrinkage complicate the detection of lakes. As a result, they selected October and November, when melting slows, lake extents stabilize, and cloud cover decreases. Further examples of learning-based studies that targeted periods with favorable observation conditions are presented in Table 1.

Strategies constrained by seasonal conditions improve data quality, reduce cloud interference, and capture stable lake conditions. However, they neglect temporal variability and the associated risk potential, which are essential in the context of non-stationary lakes that form during the melt season or during glacier surges. To address these limitations, future studies should expand training datasets with representative reference data spanning multiple seasons and develop models that learn key intra-annual variations. Multi-sensor fusion using all available and suitable satellite sources, including complementary sensors such as Synthetic Aperture Radar (SAR), can improve temporal coverage. SAR examples include Sentinel-1 (S1) [C-band, freely available], ICEYE-X1 (X-band, commercial). Augmenting the training data set or using generative models to simulate cloud penetrating synthetic imagery may also help.

2.2. Glacial lake products: types and resolutions

ML/DL-based glacial lake products differ in type, temporal resolution, and spatial resolution. Maximum Lake Extent (MLE) products, such as those by Wang and Sugiyama (2024), delineate the largest observed lake boundary, making them valuable for GLOF hazard assessment and long-term trend analysis. While straightforward to interpret, MLE overlooks short-term lake fluctuations. In contrast, Per-Pixel Classification (PPC) products, used in studies like Yuan et al. (2020), He et al. (2021) and Thomas et al. (2023), etc., capture precise water extents. When applied over time, they support the analysis of seasonal and interannual variations. Some studies, such as Xu et al. (2023), integrate both PPC and per-lake classification.

Regarding temporal resolution, Dirscherl et al. (2021) for example, produced monthly products, while Yuan et al. (2020) generated yearly products. Higher temporal resolutions (e.g., weekly or monthly) enhance the detection of seasonal changes. Conversely, lower resolutions (e.g., yearly) prioritize computational efficiency and broader trend analysis. The required temporal resolution should align with the study objective—whether focused on long-term trend analysis or short-term event monitoring, such as rapid GLOF response.

Spatial resolution also varies based on input data. High-resolution (≤3 m) products (e.g., Siddique et al., 2023; Thomas et al., 2023) are essential for mapping and monitoring small glacial lakes and resolving dynamic and detailed lake boundaries. Low-resolution (≥30 m) products (e.g., Zhao et al., 2023; Yuan et al., 2020) are efficient for large-scale, long-term global assessments. However, they may miss small lakes or subtle changes in lake extent. Medium-resolution (≈10 m) products (e.g., Basit et al., 2022; Xu et al., 2023) strike a balance between spatial detail and computational efficiency, making them well-suited for regional studies.

Balancing the need for spatial and temporal detail with resource constraints and data availability is important. We recommend selecting the appropriate product type and resolution based on the study objective.

3. Remote sensing data used: An overview

In learning-based glacial lake studies, optical satellite sensors are preferred [primarily Landsat-8 (L8) and Sentinel-2 (S2)] over radar sensors (Fig. 1). Of the 48 studies reviewed (Fig. 2), 43 (89.6%) used optical data, 16 (33.3%) used SAR data, and 12 (25%) used both (Appendix A).

Despite radar's all-weather, day-and-night imaging capabilities, optical sensors remain preferred due to their multispectral bands, which effectively capture surface water changes over time. While radar helps enhance observation frequency, optical sensors improve lake detection accuracy. The wider range of free optical data options available over the past decade – such as L8, S2, PlanetScope – compared to SAR [S1], has further reinforced this preference. Among freely available datasets, optical sensors (S2) also offer higher spatial resolution (includes 10 m bands) than SAR (S1, ≈20 m). Furthermore, SAR requires relatively extensive pre-processing before analysis (Mullissa et al., 2021). However, optical remote sensing can be affected by cast shadows and turbidity variations. On the other hand, using SAR data in mountainous regions presents challenges due to complex terrain (more details in Section 3.1). These include geometric and radiometric distortions (Rott, 1984; Wu et al., 2021) .

L8 is the most commonly used (22 papers) sensor despite its moderate spatial (30–100 m) and temporal resolution (16 days). Most L8-based studies rely on Operational Land Imager (OLI) bands. These bands provide higher radiometric resolution (12-bit), improved signal-to-noise ratio, and narrower spectral bands compared to previous Landsat missions (Mancino et al., 2020). Few exceptions (e.g., He et al., 2021; Chen et al., 2022; Kaushik et al., 2022) incorporate Thermal InfraRed Sensor (TIRS) data.

L8 is followed by S2 (20 studies) with slightly higher spatial (10–60 m) and temporal (5 days) resolution (Fig. 1, Appendix A). PlanetScope imagery is also preferred (5 papers) due its high spatial (3 m) and temporal (daily) resolution. However, its lower spectral resolution and commercial constraints restrict its broader applicability.

Among radar sensors, S1-SAR is the primary choice (15 studies), particularly the Interferometric Wide (IW) swath Ground Range Detected (GRD) mode. Topographic data such as Digital Elevation Model (DEM) are used to distinguish lake pixels from shadows and enhance classification accuracy. No strong preference for a specific DEM is observed (Fig. 1, Appendix A).

No existing studies have incorporated Surface Water and Ocean Topography (SWOT) data (Alsdorf and Lettenmaier, 2003; Vinogradova et al., 2025). SWOT's high-resolution swath altimetry enables precise monitoring of water level changes in lakes, rivers, and reservoirs (Biancamaria et al., 2016; Getirana et al., 2024). Its unique water surface elevation data provides an unprecedented opportunity to estimate lake

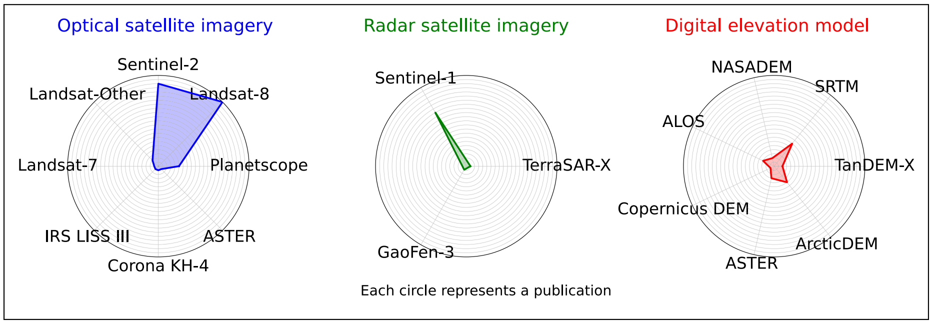


Fig. 1. Distribution of input satellite sensors (optical, radar) and topography data used in ML and DL approaches for glacial lake studies. This plot is based on 47 publications. Cao et al. (2024) was excluded as it used Google Earth imagery, comprising a mix of images from IKONOS, QuickBird, GeoEye, WorldView, SPOT, and Pleiades. More details are in (Appendix A).

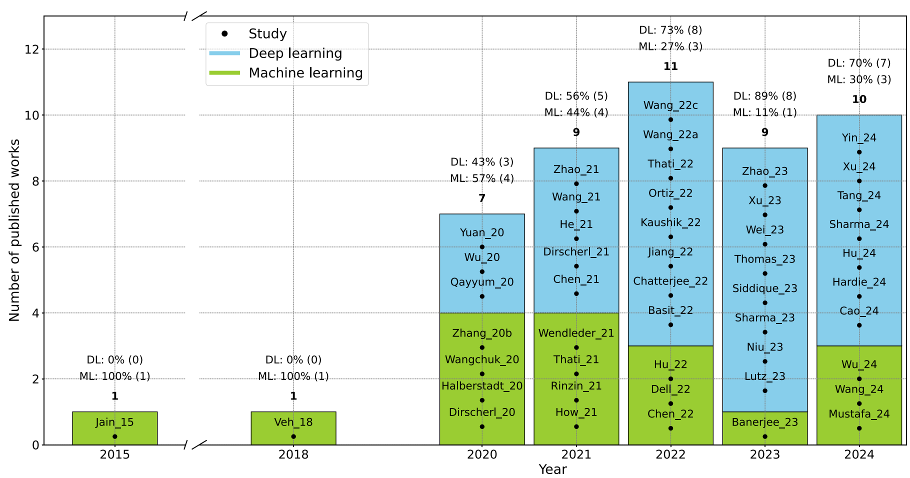


Fig. 2. Chronological histogram (till 2024) of published glacial lake studies (total: 48) that used satellite data and learning-based approaches. Total counts, category-wise counts, and percentages are annotated above each bar.

storage variations (Wu et al., 2022). This capability is valuable for assessing potential GLOF occurrences particularly in large supraglacial lakes in Greenland and Antarctica.

3.1. Single- and multi-sensor approaches: Pros and cons

ML/DL approaches have effectively used optical satellite data as standalone input for glacial lake studies in both mountainous (e.g., Basit et al., 2022; Siddique et al., 2023) and polar regions (e.g., Yuan et al., 2020; Halberstadt et al., 2020). However, their reliance on cloud-free conditions limits their applicability.

In contrast, radar-only methods have shown success only in non-mountainous regions, revealing a research gap. For example, Dirscherl et al. (2021) achieved high accuracy (F_1 *score*: 0.93) in detecting supraglacial lakes in Antarctica using S1 alone. In mountainous environments, however, radar has generally been used in combination with optical imagery (e.g., Wang et al., 2021; Wu et al., 2020). While Wang et al. (2021) achieved a satisfactory Intersection-over-Union (IoU) score (0.59) in an S1-only experiment, Wu et al. (2020) did not evaluate radar data independently.

Geometric and radiometric distortions – such as foreshortening, layover, shadowing, and backscatter variability – pose significant challenges for radar remote sensing in mountainous terrain. These distortions introduce artifacts that affect both spatial structure and pixel intensities. When present in training data, the ML/DL model may learn spurious correlations – e.g., misinterpreting terrain shadow as water – leading to a corrupted decision boundary and resulting in both false positives and false negatives. Conversely, if the model is trained on clean or corrected data but applied to distorted test scenes, its predictions may still degrade due to unseen variance in geometry or backscatter. This may also result in misclassification of actual lake pixels as background (false negatives) or surrounding terrain as lake (false positives). Novel neural network architectures optimized for SAR and enhanced pre-processing techniques are needed to mitigate these issues. However, even with these strategies, matching the accuracy of optical data will be a challenge.

Given the limitations of standalone radar data, integrating optical and SAR data has emerged as an effective strategy in mountainous regions. This approach leverages their complementary strengths to enhance classification accuracy and ensure data availability. Data-driven approaches learn rich spectral information from optical data under clear conditions and geometric features from SAR data.

Studies have demonstrated improved performance through fusion: Wu et al. (2020) observed a 4% increase in mIoU when adding S1 to L8. Additionally, Hu et al. (2024) achieved their highest IoU (0.84) when integrating S2, S1, and topographic data. Multi-sensor (including multi-mission) techniques typically rely on a primary sensor with one or more auxiliary sensors. In radar-optical fusion for high-mountain glacial lakes, optical data remains the primary input despite frequent cloud cover.

Multi-sensor fusion introduces challenges as well. First, temporal mismatches between acquisitions can complicate fusion. This was reported by Wang et al. (2021), where a 6-day gap between optical and radar data required high-level semantic fusion. Second, absolute geolocation shifts between sensors can introduce errors. For instance, Wu et al. (2020) had to address 1–2 pixel discrepancies between S1 and L8 using a mutual information-based coregistration method. Nevertheless, the benefits of multi-sensor fusion often outweigh its challenges, making it a valuable approach for glacial lake studies.

3.2. Role of sensor resolution in monitoring hazardous lakes

It is relatively more important to monitor glacial lakes that are prone to outburst floods. However, hazard potential is not determined by lake size. Numerous studies have demonstrated that GLOF impacts do not correspond to lake size and that also small to very small lakes (area <0.1 km^2) can trigger devastating outburst floods (Allen et al., 2016; Vilca et al., 2021; Sattar et al., 2022; Chen et al., 2023).

Larger lakes are detected with relatively high accuracy by underlying ML/DL models. For instance, Wu et al. (2020) reported an overall IoU of 0.62 for all lakes using L8 and S1 data, which improved to 0.8 for lakes larger than 0.1 km^2. Notably, only 17.4% of the 8262 mapped lakes exceeded this size threshold. Most glacial lakes are typically small; for example, 85.3% of Himalayan glacial lakes are under 0.1 km^2 (Wang et al., 2021). In the Eastern Himalayas, the average size is even smaller at 0.053 km^2 (Xu et al., 2023). Given their abundance, smaller lakes (i.e. smaller than 0.1 km^2) statistically experience more outbursts. Yet, their mapping and monitoring remains challenging due to detection limitations, with only few learning-based studies focusing on them. The minimum lake size considered for monitoring should be guided by the intended application.

Detecting glacial lakes smaller than 0.01 km^2 using S2 and S1 input data remains a challenge even for ML/DL approaches. This limitation, however, is more attributable to sensor resolution than to the methodologies themselves. To improve detection of these tiny lakes, integrating higher spatial-resolution satellite data, such as PlanetScope (e.g., Siddique et al., 2023; Xu et al., 2024), Pléiades, Worldview, etc., could be beneficial. Nevertheless, images from these sensors are costly, making them more suitable for individual lake studies or quality assessments rather than large-scale analysis.

Pan-sharpening the optical data could be useful too (Zheng et al., 2021). Additionally, combining Unmanned Aerial Vehicle (UAV) imagery with satellite data could support local-scale monitoring campaigns (Alvarez-Vanhard et al., 2021). However, scalability to country- or global-level would be extremely challenging, if not practically impossible.

3.3. Importance of spectral indices, atmospheric correction

Spectral indices (Montero et al., 2023) are combinations of spectral bands (e.g., ratios, normalized differences) designed to enhance specific surface properties. In the context of glacial lakes, they help highlight features such as open water, ice, or snow while reducing noise from shadows, rocks, and other interfering factors. Integrating diverse spectral indices within learning frameworks has improved glacial lake detection. This has been observed in both high mountain (e.g., Wangchuk and Bolch, 2020; Zhao et al., 2023) and polar glacier lakes (e.g., Yuan et al., 2020; Wang and Sugiyama, 2024).

Zhang et al. (2020a) found that normalized indices performed better than individual bands or band ratios. However, they also reported high correlations among indices, limiting potential accuracy gains from index combinations. In their analysis, Normalized Difference Water Index (NDWI)-G (McFeeters, 1996) outperformed other indices, including Enhanced Water Index (EWI) and NDWI-B (Huggel et al., 2002). NDWI-G [Green & Near InfraRed (NIR)] is better suited for detecting deep, clear water bodies, while NDWI-B (Blue & NIR) is more sensitive to shallow and turbid waters.

In contrast, Dirscherl et al. (2020) achieved better results with S2 bands than indices. This is likely due to atmospheric correction, which removes atmospheric effects caused by the scattering and absorption of solar radiation by atmospheric gases (Gao et al., 2009). This process prepares satellite data for remote sensing applications. Zhang et al. (2020a), on the other hand, used Top of Atmosphere (ToA) reflectance. Furthermore, among the 12 indices used, Dirscherl et al. (2020) found Tasseled Cap for Wetness (TCwet, Kauth and Thomas, 1976; Schwatke et al., 2019) and Automated Water Extraction Index ($AWEI_{nsh}$, Feyisa et al., 2014) to be more important than NDWI-G. Regional differences in pixel composition within periglacial areas, notably between Antarctica (Dirscherl et al., 2020) and Asian mountain ranges (Zhang et al., 2020a), may also have contributed to these contrasting findings.

Atmospheric correction is common in data-driven glacial lake studies (Jha and Khare, 2017; Wendleder et al., 2021; He et al., 2021; Wang et al., 2022c). However, none have quantitatively assessed its direct impact on the performance of the underlying ML/DL models. This presents a significant research opportunity. At the same time, atmospheric correction has a high computational overhead, and many ML/DL models have performed well without it (Wangchuk and Bolch, 2020; Wu et al., 2020; Zhao et al., 2023; Hardie et al., 2024, etc.). Hence, an initial investigation using ToA reflectance is recommended before conducting a detailed analysis.

4. Learning-based approaches for glacial lake studies

Glacial lake studies based on remote sensing rely primarily on spectral indices and/or backscatter/reflectance thresholds. However, such approaches often require threshold adaptation for large-scale analyzes and multi-temporal monitoring (Jawak et al., 2015; Wangchuk and Bolch, 2020). While generally effective, these methods face significant challenges in mountainous environments. Complex terrain, varying weather conditions, changes in glacier dynamics, and seasonal variations in mountains contribute to notable inaccuracies in identifying glacial lakes (Bolch et al., 2011). Moreover, such methods often neglect contextual information from neighboring pixels or temporal sequences. They make decisions solely based on individual pixel values. Consequently, ML/DL approaches have become widespread.

4.1. Chronological progression & methodological distribution

The first learning-based glacial lake study (Jain et al., 2015), published a decade ago, used ASTER multispectral imagery. They used a Support Vector Machine (SVM) classifier for the semi-automatic detection of glacial lakes in the Chamkhar Chu Basin, Hindukush Himalaya, Bhutan.

Of the 48 studies surveyed (Appendix B), 31 (64.6%) employed DL approaches, while 17 (35.4%) used classical ML techniques (Fig. 2). This reflects the field's growing preference for DL methodologies. Although DL is a subset of ML, they are addressed separately in our review to highlight distinct trends.

Most studies on glacial lakes applying ML or DL were published in 2022 (11 papers), with at least seven DL articles consistently appearing each year since 2022. Fig. 2 provides a chronological overview of the literature. It includes both published papers and a book chapter (Thati et al., 2021) up to 2024. Fig. 3 illustrates the distribution of methodologies reported in these studies.

Research output grew substantially since 2020, coinciding with the introduction of the first DL-based approach (Yuan et al., 2020). This study used a CNN classifier and L8 imagery to detect supraglacial lakes in Southwest Greenland. 46 out of the 48 studies were published from 2020 onward, underscoring the growing focus on learning-based approaches in glacial lake remote sensing.

In ML/DL, classification predicts discrete class categories, while regression estimates continuous numerical values (Bishop, 2006). As of 2024, all learning-based approaches for glacial lake studies have been classification-based, with no reported use of regression models.

Among classification-based methods, CNN (Lecun et al., 1998) variants are predominant (Appendix C). U-Net (Ronneberger et al., 2015) is the most widely applied CNN architecture (Fig. 3). DeepLab (Chen et al., 2015, 2018a,b) variants (Appendix D), known for their advanced semantic segmentation capabilities, are relatively less explored. This is likely due to the additional resources required to train these relatively parameter-heavy models, which demand large, representative datasets. Among ML approaches, Random Forest (RF) and SVM are widely used (Cortes and Vapnik, 1995; Breiman, 2001; Mountrakis et al., 2011).

4.2. Distribution of study sites and model transferability

Glacial lakes are predominantly located in glaciated mountain regions, particularly at medium-to-high latitudes, as well as in the polar lowlands (Shugar et al., 2020). Over 80% of these lakes are concentrated in Greenland, the Alaska Range, Southern Andes, High Mountain Asia (HMA), and the eastern Canadian Arctic (Zhang et al., 2024). Despite this broad distribution, ML/DL-based studies on glacial lake mapping and monitoring have primarily focused on a limited subset of these regions, highlighting significant research gaps. Table E.6 (Appendix E) presents key regions with glacial lakes, notable publications that investigated them, and ML/DL studies that considered these regions as primary study sites. It also includes studies that evaluated the transferability of their ML/DL models in these regions, even if they were not the primary study sites.

HMA has received the most research attention from learning-based approaches, followed by Greenland and Antarctica (Appendix E). This geographic trend aligns with findings by Calamita et al. (2024). They reported that remote sensing is underutilized in studying lake ecosystem shifts in Europe (1%) and North America (5%). However, it is significantly more applied in Asia (23%) to monitor climate-related changes in lakes.

In contrast, several regions with significant GLOF activity remain understudied despite documented evidence. Historically, more than 60% of GLOFs have occurred in Alaska, HMA, and Iceland (Zhang et al., 2024). Northern Andean glacial lakes have also produced several GLOFs. The volume of Patagonian lakes (excluding the three largest) more than doubled from 1990–1999 to 2015–2018 (Shugar et al., 2020).

The risk associated to GLOF hazards is a key reason for this uneven geographic distribution of ML/DL-based glacial lake mapping studies. High-latitude regions have the highest number of glacial lakes, strongest lake growth rates (Shugar et al., 2020) and probably also experience most GLOF events. However, the impacts of GLOFs in terms of damage and loss – and thus GLOF risk – is much higher in lower- and mid-latitude mountain regions. This is due to both the higher concentration of people and infrastructure exposed to GLOFs, and, related, also higher vulnerabilities to GLOFs of societies in these densely populated mountain ranges (Taylor et al., 2023). This is further evidenced by the fact that even smaller lakes can cause major disasters in Andes (Vilca et al., 2021) or the Alps (Huggel et al., 2003). HMA is the only region that is a hotspot of GLOF risk and well studied in terms of ML/DL-based solutions for glacial lake mapping.

Research on the Andes remains limited, with only Wangchuk and Bolch (2020) conducting a dedicated study. Additionally, Qayyum et al. (2020) and Tang et al. (2024) included Andes in their transferability assessments. Similarly, the European Alps have been the focus of only one study. Wangchuk and Bolch (2020) examined the Andes and the Swiss Alps, however the study primarily focused on six locations in HMA.

Other key regions, such as the Canadian and Russian Arctic, Scandinavia, Iceland, and New Zealand, remain unexplored using learning-based approaches, possibly due to lower risks associated with the abundant number of glacial lakes in these regions. This reveals a research opportunity not only to improve spatial coverage but also to enhance training datasets and advance algorithm development. Interestingly, the fastest-growing lakes (in terms of areal expansion) are located in Iceland, the Russian Arctic, and Scandinavia (Shugar et al., 2020). These regions offer valuable testbeds for developing and evaluating new glacial lake mapping methods, which can later be applied to high-risk regions. Comprehensive study of such regions is beneficial for building generalizable, globally robust approaches.

To further examine the spatial trends of ML/DL studies, we investigate geographical distribution of the methodologies. The reviewed approaches are categorized into six groups in Fig. 4: three for DL (U-Net, other CNNs, and other DL methods) and three for ML (RF, SVM, and other ML methods). Each continent is represented by a distinct bar plot. Each methodology is counted only once per continent, even if multiple study sites within the same continent were analyzed. For instance, Zhao et al. (2023), who assessed over 5 sites in HMA using a CNN, is considered a single entry. However, studies that applied multiple algorithms to the same site (e.g., Halberstadt et al. (2020)) are counted separately for each methodology used. Similarly, studies applying the same algorithm in different continents (e.g., Wangchuk and Bolch (2020)) are counted separately for each continent considered.

Two DL studies (Chatterjee et al., 2022; Thomas et al., 2023) were excluded from Table E.6 (Appendix E) and Fig. 4. Although Chatterjee et al. (2022) included Lake Tibet, a glacial lake, their primary focus was on non-glacial lakes. Similarly, Thomas et al. (2023) investigated supraglacial lakes across the Arctic without specifying distinct study sites, making their inclusion in our region-clustered spatial distribution analysis difficult. However, both studies remain part of the broader methodological assessment.

DL techniques, particularly U-Net and other CNNs, are more commonly applied in HMA (Fig. 4). ML methods like RF and SVM are also more frequently used in HMA. However, they have a relatively stronger presence in Antarctica compared to DL.

Regardless of the technique, such data-driven models, if trained on small or non-representative datasets, risk overfitting. This reduces their effectiveness when applied to previously unseen regions or time periods. Therefore, ensuring spatiotemporal transferability is crucial for enhancing model robustness.

Many learning-based methods have been confined to their primary study sites. However, some notable exceptions assess spatial transferability by training on one continent and testing on another (Table E.6, Appendix E). For instance, Wangchuk and Bolch (2020) developed their approach for the Himalayas and tested it in the Alps and Andes. Their qualitative results from the Andes aligned with datasets from the National Water Authority of Peru. Similarly, Dirscherl et al. (2021) evaluated their model's generalizability (trained on data from Antarctica) by applying it to supraglacial lakes in Southwest Greenland.

Although the qualitative results of Dirscherl et al. (2021) were promising, large supraglacial lakes common in Greenland were underrepresented in their training dataset. This led to overfitting despite extensive data augmentation (Section 4.5.3). Fine-tuning with representative data from Greenland could improve the performance. However, this was not tested or reported. Likewise, Tang et al. (2024) trained their model on 15 mountain ranges in the Third Pole region and, after fine-tuning, demonstrated its qualitative generalization to the Patagonian Andes, Alaska, and Greenland. However, none of these studies provided quantitative validation in their transferability experiments. This highlights a key gap in assessment.

Temporal transferability is equally critical, as models must maintain performance when applied to data from the same study site across different time periods. It is less challenging in stable environments. However, it becomes significantly harder in rapidly changing conditions, requiring models to adapt to both periodic (seasonal) and non-periodic (long-term) changes. An example is Dirscherl et al. (2020), who investigated the spatiotemporal transferability of their RF model. They trained it on supraglacial lake occurrences from summer 2019 across fourteen regions. Evaluation was conducted on eight spatially independent regions from summers 2017 and 2018 across the Antarctic ice sheet. Their model achieved impressive average F_1 *scores* of 0.997 for the non-water class and 0.86 for the water class.

Models that generalize effectively across diverse spatial and temporal contexts are essential but not yet standard practice. Future studies should prioritize comprehensive spatiotemporal transferability assessments, incorporating both quantitative and qualitative evaluations. Openly sharing datasets and ground truth annotations will further support these efforts. It will foster collaboration and enable more rigorous model development and evaluation.

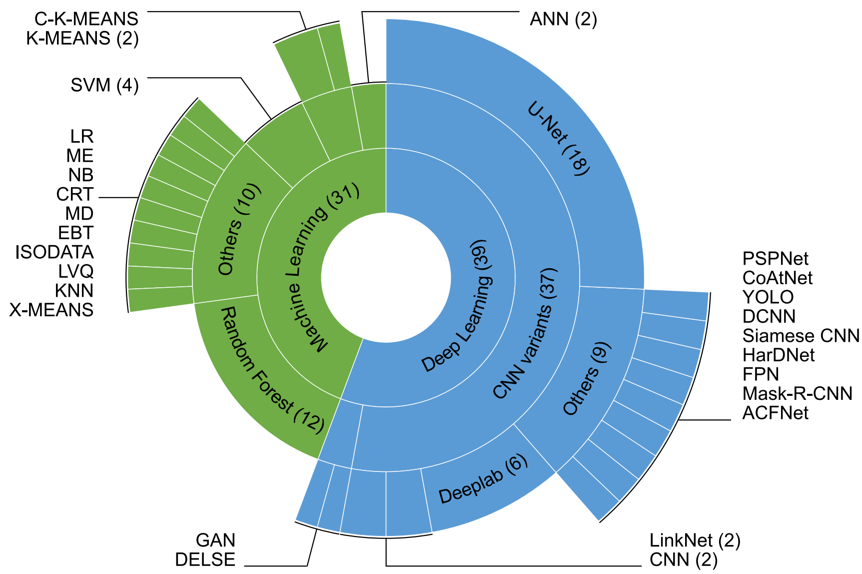


Fig. 3. Distribution of ML (31 methodologies) and DL (39 methodologies) approaches proposed in 48 studies on glacial lakes using satellite data. Deeplab includes its variants; methods without numbers in brackets were each used once. More details are in (Appendix C). Refer to the glossary (Appendix G) for full forms.

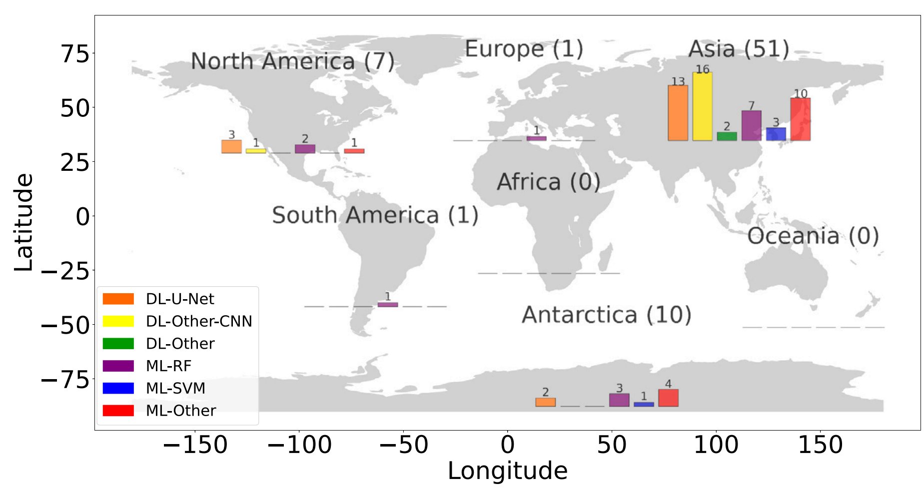


Fig. 4. Continent-wise distribution (primary study site only) of ML/DL methodologies (six categories: 3 each for DL and ML) used in glacial lake remote sensing studies. Background map credit: https://www.naturalearthdata.com/. Refer to the glossary (Appendix G) for full forms.

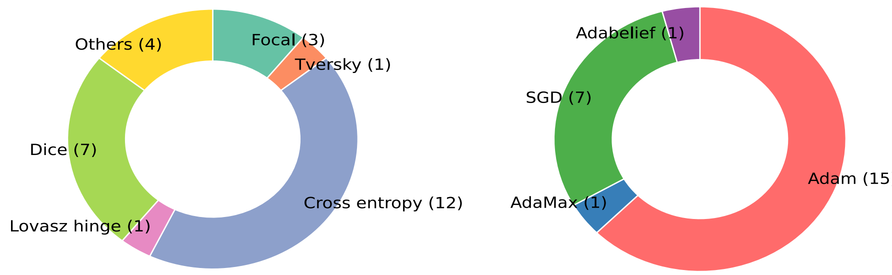
4.3. Strong vs. weak supervision: Challenges, opportunities

Most of the glacial lake studies that apply ML/DL methodologies (Fig. 3) rely on supervised learning, which depends heavily on labeled datasets. However, generating ground truth annotations is time-consuming and resource-intensive. To mitigate this, it is essential to develop more efficient methods for generating reference labels. Another approach is to adopt weakly supervised learning (Chapelle et al., 2009; Karamanolakis et al., 2021), which uses minimal, noisy, or incomplete labels. This will reduce annotation effort, enabling broader and more scalable application of ML and DL analyses. Additionally, it will help fully leverage the vast and ever-growing volumes of available remote sensing data. An example is Ortiz et al. (2022), who applied varying degrees of weak supervision. They employed historically guided U-Net, morphological snakes, and DEep Level Set Evolution (DELSE), based on the assumption that glacial lakes evolve gradually over time. They used low-resolution historical glacial lake labels to guide the segmentation of more recent high-resolution satellite imagery and Bing maps. Similarly, Zhao et al. (2023) introduced weak supervision using NDWI within a contrastive loss-based Siamese neural network. They learned glacial lake representations by maximizing the similarity between input satellite images and their augmentations, requiring no ground truth and only minimal supervision. However, the full potential of weakly supervised learning remains systematically underexplored in glacial lake studies. This presents a significant research opportunity.

4.4. Class categories, imbalance

Most supervised approaches formulate binary classification tasks to distinguish glacial lake pixels from the background. A few exceptions (Veh et al., 2018; Dirscherl et al., 2020, 2021; Halberstadt et al., 2020; Wendleder et al., 2021) incorporated additional classes like snow/ice, shadow, rock/land/sediment, debris, slush, firn, and cloud. Halberstadt et al. (2020) included even fine-grained classes such as blue ice, flowing ice, shallow lakes, deep lakes, cloud shadow, sunlit rock, and shadowed rock. In rare cases, the number of classes varied based on input data. For instance, Dirscherl et al. (2021) applied binary classification for S1 data but four-class classification for S2 data.

Both binary and multi-class classification can achieve accurate lake detection. Binary approaches are often simpler. Multi-class methods offer the added benefit of detailed surface characterization, at the cost of higher-quality training data and more complex models.



(a) Loss functions (based on 24 publications) (b) Optimization strategies (23 publications)

Fig. 5. Distribution of hyperparameters in deep learning-based glacial lake studies (number of publications in brackets). Some studies reported multiple loss functions (Basit et al., 2022; Cao et al., 2024) or optimizers (Chatterjee et al., 2022). More details are in (Appendix F).

When framed as a two-class problem, the "lake" class is typically underrepresented, leading to class imbalance (He and Garcia, 2009). This uneven class distribution can bias the model toward the majority class: "background", resulting in poor performance on the minority class.

Standard strategies to address class imbalance include tailored loss functions (Section 4.5.1), strict evaluation metrics (Section 4.6), class-dependent data augmentation (Section 4.5.3), and undersampling the majority class (Dirscherl et al., 2020; Yuan et al., 2020). Regardless of the strategy employed, addressing class imbalance is crucial in glacial lake studies and is strongly encouraged.

4.5. Deep learning approaches

4.5.1. Loss functions and optimization schemes

A loss function quantifies the difference between a model's predictions and the actual ground truth labels, guiding the optimization process during model training (Wang et al., 2022b). By minimizing the loss, the model iteratively adjusts its parameters to improve predictions. In glacial lake studies, cross-entropy (He et al., 2021; Kaushik et al., 2022, etc.) and Dice loss (Li et al., 2020; Hu et al., 2024, etc.) functions are the most commonly used (Fig. 5).

Cross-entropy is well-suited for multi-class classification, providing a straightforward approach to measure the divergence between predicted probabilities and true labels (Zhang and Sabuncu, 2018). It is also effective for binary classification. To address class imbalance, several glacial lake studies (Ortiz et al., 2022; Hardie et al., 2024, etc.) successfully employed weighted variants of cross-entropy. These variants assign higher weights to minority "lake" class samples during model training.

For binary semantic segmentation tasks, dice loss is particularly effective. It directly optimizes the overlap between predicted and actual foreground regions, mitigating the impact of class imbalance. While it can be extended to multi-class segmentation by computing per-class dice scores, its ability to balance foreground and background contributions makes it especially valuable in tasks like glacial lake detection (Sudre et al., 2017). Tversky loss (Wu et al., 2020), an extension of dice loss, further enhances flexibility. It adjusts penalties for false positives and false negatives, making it useful when prioritizing precision or recall (Salehi et al., 2017).

Optimization strategies complement loss functions. Adaptive Moment (AdaM) is widely used (Fig. 5), followed by Stochastic Gradient Descent (SGD). AdaM combines the benefits of adaptive learning rates and momentum. This makes it particularly effective in handling sparse gradients or non-stationary objectives (Kingma and Ba, 2015).

Advanced variants like AdaMax and AdaBelief have been explored by Dirscherl et al. (2021) and Chatterjee et al. (2022), respectively. AdaMax extends AdaM to work effectively with infinite norms. It offers greater stability in sparse gradient scenarios and non-convex optimization (Kingma and Ba, 2015). AdaBelief modifies the second-moment estimation, leading to faster convergence and better generalization (Zhuang et al., 2020).

In contrast, SGD is used due to its relative simplicity and effectiveness in large-scale problems. It is especially useful when computational efficiency is critical (Bottou, 2010). However, in its basic form, SGD may struggle with convergence on complex loss surfaces. Enhancements like momentum or learning rate scheduling, as demonstrated by some glacial lake studies (Yuan et al. (2020), Wang et al. (2021) and Hu et al. (2024)), can address these issues.

In glacial lake studies, depending on the number of classes, it is recommended to use any of the above loss functions that effectively tackle class imbalance. SGD optimization with momentum is recommended for large datasets or when resources are limited. AdaM variants are encouraged for complex, sparse data requiring quick model convergence.

4.5.2. Pre-training, transfer learning, & model adaptations

Instead of training from scratch, fine-tuning a DL model pre-trained on a large, labeled dataset mitigates issues like slow convergence and overfitting. Transfer learning allows adapting pre-trained model weights, reducing the need for extensive labeled data while enhancing generalization.

In satellite remote sensing, transfer learning is facilitated by publicly available large-scale datasets. Examples are *BigEarthNet* (Sumbul et al., 2021), *EuroSAT* (Helber et al., 2019), *SpaceNet* (Shermeyer et al., 2020), and *ImageNet* (Deng et al., 2009; Krizhevsky et al., 2017). These datasets allow models to learn fundamental spatial features – such as edges, textures, and object structures – which can be repurposed for tasks like glacial lake segmentation (Weiss et al., 2016).

For instance, Qayyum et al. (2020) employed transfer learning for glacial lake mapping. They used *EfficientNet* (Tan and Le, 2019) as the backbone for a U-Net model, fine-tuning its higher layers for glacial lake detection.

Transfer learning is effective even when the original and target tasks differ significantly. While this capability has been extensively explored in related fields, such as lake ice monitoring, transfer learning remains underutilized in glacial lake studies. For instance, Tom et al. (2022) demonstrated that a DeepLabv3+ model pre-trained on close-range imagery for a computer vision task could be successfully adapted for lake ice monitoring using SAR satellite data. This exemplifies the versatility of transfer learning and presents a promising avenue for glacial lake remote sensing research.

One challenge is that most DL models used for glacial lake studies were originally designed for generic computer vision tasks. Such models typically support only 3–4 input channels (e.g., RGB, RGB-depth). This design choice simplifies transfer learning but restricts the ability to fully exploit multispectral, hyperspectral, and radar-based remote sensing data. Only a few studies used more than four channels (Wu et al., 2020; He et al., 2021; Hu et al., 2024; Tang et al., 2024). Others have worked around this limitation by empirically selecting the most relevant input spectral features (Section 3.3) or using automated feature importance analysis. However, such approaches may not have exploited the full potential of multi-source remote sensing data.

Expanding model architectures to accommodate a greater number of input channels, such as a dozen or more spectral bands, is technically straightforward. However, it presents a trade-off. While such modifications enhance the model's ability to process diverse remote sensing data, they prevent the direct reuse of pre-trained weights, necessitating training from scratch. This increases computational costs and the risk of overfitting.

Furthermore, standard DL architectures are not optimized for radar-specific features such as phase, backscatter, and polarization. This underscores the need for task-specific model adaptations. Therefore, to maximize the benefits of transfer learning for large-scale, data-efficient glacial lake studies, it is necessary to redesign existing architectures. These should accommodate a wider range of remote sensing inputs while still leveraging pre-trained feature representations.

4.5.3. Importance of data augmentation

Augmentation in DL is a strategy to mitigate data scarcity. By transforming existing data, this technique expands and diversifies the training dataset. It improves model robustness, generalization, and efficiency through exposure to diverse data variations, all without requiring additional data collection or labeling. However, the effectiveness of augmentation strategies remains largely empirical and highly dependent on the dataset and model.

Glacial lake studies have applied spatial transformation operations such as patch flipping (Wang et al., 2022c, etc.), patch rotation (Cao et al., 2024, etc.), and patch mirroring (He et al., 2021, etc.). Spectral distribution modifications were also explored. Wu et al. (2020) adjusted image saturation and brightness. Zhao et al. (2023) employed techniques like color jittering, random erasing, blurring, noise addition, and grayscale adjustments.

In Dirscherl et al. (2021), augmentation strategies were tailored per patch depending on the number of lake pixels in each patch. To address class imbalance, they oversampled the image patches with the underrepresented 'lake' class. Additionally, they augmented challenging non-water patches (wet snow, shadow pixels, etc.).

Notably, only a few papers quantitatively evaluated the performance impact of individual operations. For instance, Zhao et al. (2023) found that spatial transformations (F_1 *score*: 0.66) slightly outperformed spectral modifications (F_1 *score*: 0.65). Among individual techniques, image flipping was most effective (F_1 *score*: 0.68), followed by color jittering (F_1 *score*: 0.67) and image rotation (F_1 *score*: 0.66). Based on these findings, they adjusted the probabilities of different augmentations to prioritize the most impactful ones.

Augmentation is a common practice in glacial lake studies. However, due to the limited number of studies that evaluate the impact of specific techniques quantitatively, it is difficult to generalize their utility across models and datasets. Future studies should systematically evaluate and optimize augmentation strategies.

4.5.4. Recommended strategies

Table 2 outlines recommended DL strategies for glacial lake detection under different scenarios. While outcomes may vary with model architecture and dataset characteristics (e.g., sensor type and resolution, region, class distribution, reference label noise), these strategies serve as empirically grounded starting points for method selection and adaptation.

Combining weak supervision (Section 4.3) with transfer learning (Section 4.5.2) offers a promising research direction. Ultimately, model selection should be driven by data availability. Supervised methods like U-Net are well-suited for data-rich environments if no transfer learning is involved. However, in data-scarce regions, weakly supervised approaches and pre-trained DL architectures offer viable alternatives.

Though DL has emerged as an exceptionally powerful tool in glacial lake remote sensing, there are some constraints. Firstly, DL models are relatively data-hungry, requiring large amounts of annotated reference data for training. Nevertheless, given the statistical nature of DL methodologies, performance improves with a broader and more diverse training dataset. However, fine-tuning may be necessary when applying such models to new regions or time periods. Secondly, DL methods require substantial computational resources, typically demanding powerful Graphics Processing Unit(s).

4.6. Choosing right evaluation metrics

Standard metrics such as recall (producer's accuracy), F_1 *score*, precision (user's accuracy), IoU, and overall classification accuracy are the most commonly used in learning-based glacial lake studies. These metrics are depicted by the larger circles in Fig. 6. Recall measures the proportion of actual glacial lakes correctly identified, regardless of false positives. Conversely, precision evaluates the proportion of detected lakes that are actual lakes, reducing false identifications. IoU measures the overlap between predicted and actual truth, providing a robust metric for image segmentation tasks. The F_1 *score* balances precision and recall. Overall accuracy reflects the proportion of correctly classified pixels (both lake and background) in relation to the total number of pixels in the dataset.

Some studies employ specialized metrics. For instance, the Tversky index (Wu et al., 2020) is designed to handle class imbalance while the Fréchet distance (Ortiz et al., 2022) measures shape similarity. The coefficient of determination (Kaushik et al., 2022) evaluates the agreement between the predicted and reference lake boundaries. These tailored metrics highlight a growing interest toward addressing nuanced aspects of performance evaluation.

Overall classification accuracy was relatively more commonly reported in early ML/DL studies (Fig. 6). However, overall accuracy alone is inadequate for class-imbalanced datasets, as it can misleadingly inflate performance results. Metrics such as IoU, F_1 *score*, precision, recall, and the Tversky index, which are robust to class imbalance, are strongly recommended. While overall accuracy can provide useful context when combined with these stricter metrics, it should not be reported in isolation.

Additionally, some studies (He et al., 2021; Chen et al., 2022, etc.) reported the Kappa coefficient (Fig. 6). However, Pontius and Millones (2011) highlighted that Kappa indices can be misleading or flawed, particularly in remote sensing applications. These indices compare accuracy against a baseline of randomness, which is an unrealistic reference for map construction. This makes Kappa coefficient difficult to interpret and, in some cases, undefined. Consequently, its use is not recommended. The recent trend of reduced Kappa coefficient usage relative to other metrics (Fig. 6) aligns with this recommendation.

4.7. Performance inter-comparison: Insights, gaps, challenges

When proposing a novel glacial lake product, it is essential to benchmark its performance both quantitatively and qualitatively. This comparison should be made against existing state-of-the-art methods to substantiate performance gains. However, existing comparisons often differ in datasets, learning strategies, and evaluation metrics. This makes it difficult to draw definitive conclusions.

Qayyum et al. (2020) compared their U-Net model with *GLakeMap* (Wangchuk and Bolch, 2020), an RF-assisted rule-based thresholding approach. Both methods performed well on large lakes. However, U-Net outperformed *GLakeMap* on small lakes. This is likely due to the higher spatial resolution of PlanetScope (3 m) compared to S2 (10 m) used by the latter.

In contrast, using S2 data, Basit et al. (2022) outperformed (IoU 0.8 vs. 0.71) Siddique et al. (2023), who relied on PlanetScope imagery. Interestingly, both used a U-Net model with an *ImageNet*-pretrained

Table 2
DL recommendations for glacial lake detection under common application scenarios. CE stands for Cross Entropy.

Extreme class imbalance:
• Use loss functions such as Focal, Tversky, Dice, weighted CE (avoid unweighted CE).
• Augment the training set to increase underrepresented class samples.
• Optimizers do not directly address class imbalance. However, Adam and SGD with momentum can support stable and faster convergence when used with imbalance-aware loss functions. Examples: Focal/Tversky + Adam, Dice + SGD (with momentum).
Data scarcity:
• Use transfer learning and data augmentation.
• When training from scratch, prefer relatively lightweight models (e.g., U-Net with *MobileNetV2* or *EfficientNet-B0* encoders) over deeper architectures like DeepLabv3+.
• Optimizers like Adam can accelerate convergence on small datasets, but may require strong regularization (e.g., dropout) to prevent overfitting.
Limited computational resources:
• Use models with lightweight backbones (e.g., U-Net or DeepLabv3+ with *MobileNetV2* or *EfficientNet-B0*).
• Use computationally efficient loss functions such as weighted CE together with memory-efficient optimizers like SGD (with momentum). While Adam may converge faster, it has relatively higher memory overhead and should be used selectively.
Small lake detection:
• Use attention-based models (e.g., attention U-Net by He et al., 2021), noting added computational cost.
• Use DeepLabv3+ with Atrous Spatial Pyramid Pooling (ASPP). Skip connections (in U-Net) and multi-scale context (in DeepLabv3+) enhance small target detection.

EfficientNetB0 backbone. Several factors likely contributed to these performance differences. While spatial and spectral resolution both influence model performance, their impact also depends on the training strategy. *EfficientNetB0*, optimized for larger datasets, may have underfitted on PlanetScope's limited spectral bands, hindering its ability to learn discriminative features. While PlanetScope offers finer spatial resolution, it lacks broader spectral coverage, particularly in the ShortWave InfraRed (SWIR) range. This limitation could reduce lake-background separability. The datasets also differed in size (1200 images for Basit et al. (2022) vs. 3525 for Siddique et al. (2023)). The loss function used also varied, with Basit et al. (2022) employing both *focal* and *Jaccard* loss, while Siddique et al. (2023) used only *focal* loss. The use of *Jaccard* loss, which directly optimizes for IoU, likely contributed to Basit et al. (2022)'s higher performance.

Some studies have compared DL models with ML counterparts and thresholded spectral indices. For instance, Qayyum et al. (2020) compared their *Efficient-U-Net* (CNN) model against standard ML models. They reported an F_1 *score* of 0.94, significantly outperforming SVM (0.78) and RF (0.75). This highlights the advantages of U-Net.

Similarly, Wu et al. (2020) compared their U-Net model with RF and thresholded Modified Normalized Difference Water Index (MNDWI). They found that both U-Net and RF outperformed MNDWI in cases involving mountain shadows and frozen lakes. Their U-Net model effectively learned the spatial relationships between neighboring pixels. U-Net exhibited fewer misclassifications in low-reflectivity areas compared to RF.

Some DL-based studies have reported modest results as well. For example, Yuan et al. (2020) evaluated CNNs against RF and SVM, however observed only marginal improvements. This was because the number of test samples was not sufficient. Interestingly, all three approaches (CNN, SVM, RF) achieved more than 98.5% overall accuracy, recall and precision. This indicates a weak test set rather than an inherent shortcoming of CNN, thereby limiting the ability to discern meaningful differences in performance.

Few studies have systematically evaluated different deep learning architectures and backbone choices. For instance, He et al. (2021) incorporated a self-attention mechanism (Vaswani et al., 2017; Ghaffarian et al., 2021) into U-Net. This resulted in only a slight improvement (F_1 *score*: 0.69) compared to the baseline U-Net (F_1 *score*: 0.68). Similarly, Hu et al. (2024) enhanced U-Net by integrating a residual attention mechanism. This led to a 1.5% increase in F_1 *score* and a three-fold acceleration in convergence. Wang et al. (2021) introduced *ACFNet*, comparing it against Wu et al. (2020)'s U-Net and achieving a higher F_1 *score* (0.91 vs. 0.88). While incremental, these improvements highlight the potential impact of architectural enhancements in DL models.

Cao et al. (2024) conducted a comprehensive comparison of SVM, RF, U-Net, U-Net with an *EfficientNet* backbone, and *LinkNet* variants. SVM had the lowest IoU (0.67). L12-*LinkNet50* with heavy post-processing [SLIC superpixel and Dense Conditional Random Field (CRF)] achieved the highest (0.91). RF, U-Net, and *EfficientNet* obtained IoUs of 0.68, 0.70, and 0.78, respectively. This study highlighted the importance of post-processing. Additionally, their findings demonstrated that combining multiple loss functions, such as *Lovász hinge* and *dice* loss, improves semantic segmentation performance.

Various studies have shown that DeepLab variants outperform U-Net. For instance, on a dataset that includes glacial lakes from the Third Pole region, Tang et al. (2024) compared multiple variants of DeepLab and U-Net. They found that DeepLabv3+ with a *MobileNetV3* (Howard et al., 2019) backbone achieved the highest performance (IoU: 0.95). Their evaluation included challenging conditions such as mountain shadows, frozen lakes, and wet ice. Other DeepLabv3+ variants with *ResNet50* (He et al., 2016), *Xception* (Chollet, 2017), and *MobileNetV2* (Sandler et al., 2018) backbones followed closely (IoU: 0.94). U-Net variants performed slightly lower: *ResNet50* (0.93), *MobileNetV3* (0.92), and *MobileNetV2* (0.92). The study demonstrated that for the same backbone, DeepLabv3+ consistently outperformed U-Net.

Siddique et al. (2023) also improved the IoU from 0.71 to 0.73 by switching to a DeepLabv3+ model (backbone: *MobileNetV2*) from U-Net (backbone: *EfficientNetB0*). U-Net's skip connections enable the fusion of low-level appearance details with high-level semantic features. This is important for accurately delineating lake boundaries, especially for small glacial lakes, because the skip connections preserve fine-grained spatial information by reintroducing high-resolution encoder features into the decoder (Fig. 7(a)). However, they can also propagate redundant information, potentially introducing noise irrelevant to glacial lake segmentation. In contrast, DeepLabv3+ employs ASPP, which applies parallel dilated convolutions at multiple scales to enhance multi-scale feature extraction (Fig. 7(b)). Each dilation rate captures features over a different receptive field size. This allows the model to recognize small lakes based on fine textures, large lakes based on broad spatial context, and lakes with complex geometries by combining structural information at multiple scales. This improves detection performance across a wide range of lake sizes and shapes.

A notable gap remains in ensuring fair and comprehensive comparisons among methodologies. Some ML/DL methods (e.g., Xu et al., 2023) have been compared only with thresholded spectral indices rather than against other state-of-the-art ML/DL approaches. In few cases (e.g., Dirscherl et al., 2020, 2021), there is no comparative analysis at all.

For a fair comparison, the approach being proposed should be evaluated at a study site where a high-performing method has already been tested. This is important because state-of-the-art algorithms might have been developed for entirely different regions. Alternatively, at least one such method may be implemented and evaluated on the region of interest. Despite the time and effort involved, such comparisons are essential for establishing the credibility of new approaches. Accordingly, they are strongly recommended.

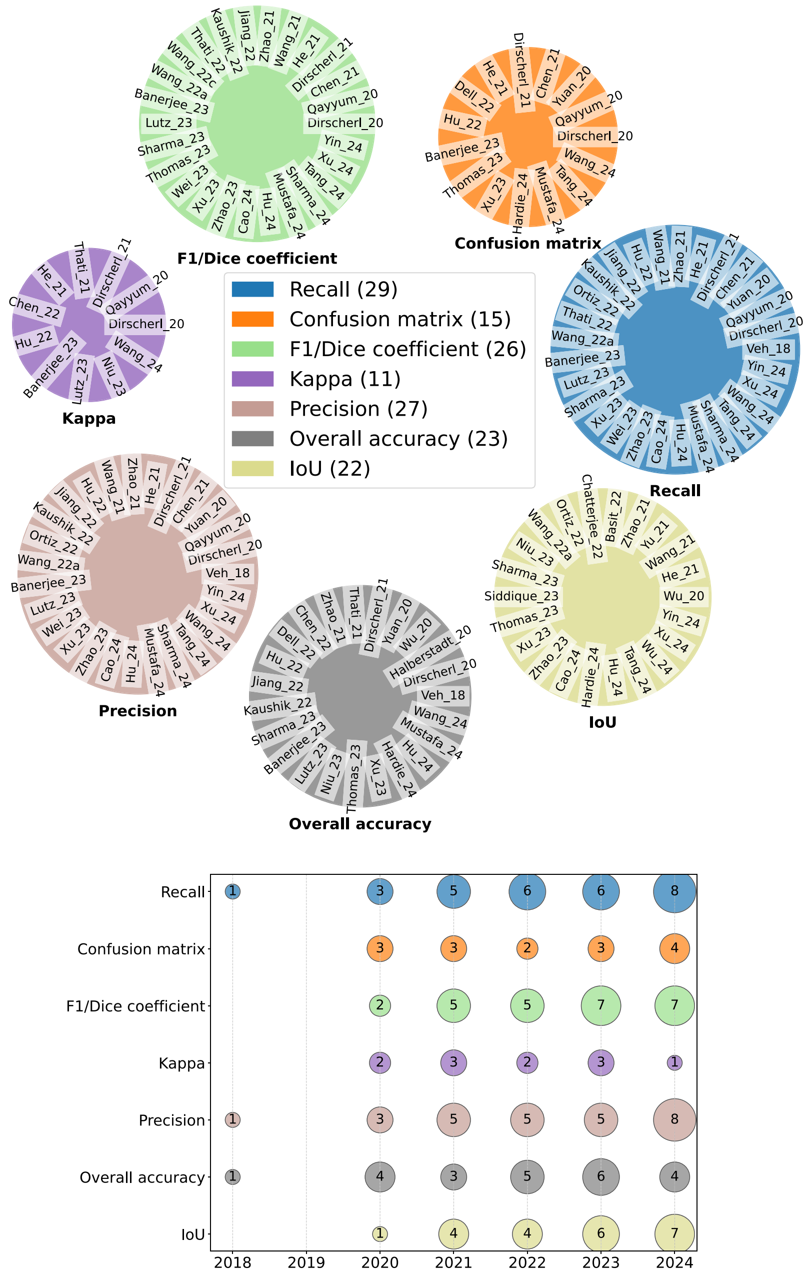


Fig. 6. Distribution (top) and yearly trend (bottom) of evaluation metrics based on 41 publications which reported detailed quantitative analysis. The legend indicates number of studies (in brackets) that used each metric, and circle radius reflects the usage frequency. Papers employing each metric are listed within respective circles.

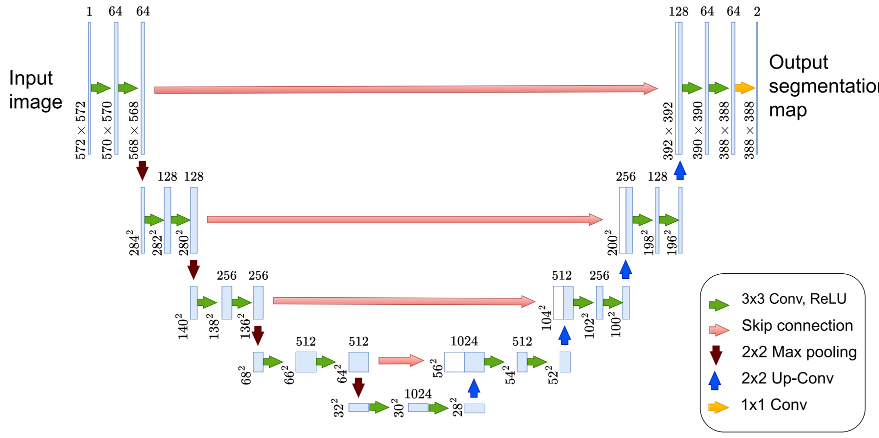
A comprehensive comparison of top-performing methodologies on a fixed dataset is notably absent from the literature. Comparing *ACFNet* (Wang et al., 2021) with Cao et al. (2024)'s highest-performing *LinkNet* and Tang et al. (2024)'s best-performing DeepLabv3+ would provide valuable insights. Achieving this requires representative training datasets, along with rigorous cross-regional evaluations, model exchange, and standardized benchmarking protocols. Its findings could inform a truly generalizable ML/DL approach for global-scale glacial lake mapping and monitoring.

Ensuring reproducibility and transparency through open science practices is crucial for advancing intercomparisons in glacial lake research. Initiatives like NASA's Transform to OPen Science (TOPS, https://doi.org/10.5281/zenodo.10161527) lead the way in promoting open science. Some glacial lake studies have embraced this by making their code and/or data publicly accessible (Ortiz et al., 2022; Wang et al., 2022a, etc.), promoting transparency. However, majority of studies still do not, making it difficult to access datasets and reproduce results, particularly for researchers or end-users with limited programming expertise.

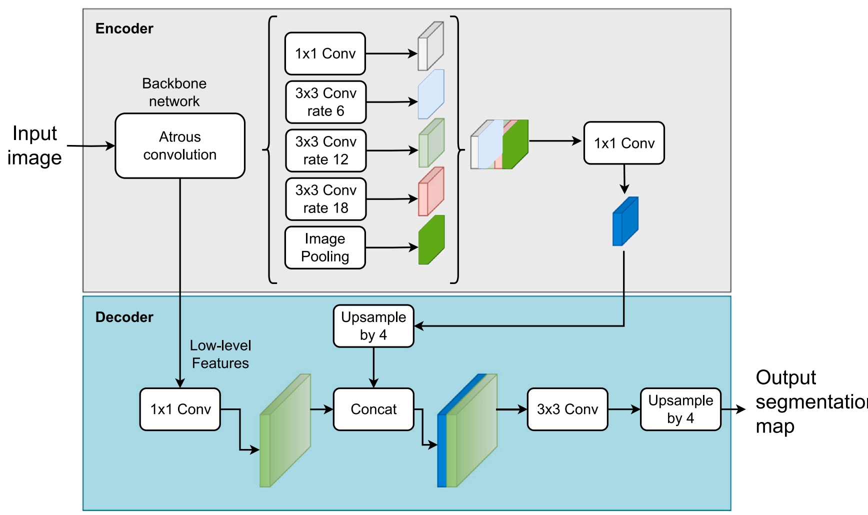
5. Discussion

DL methods are preferred over classical ML for glacial lake studies, comprising nearly two-thirds of reported papers and more than 50% of the proposed methodologies (Figs. 2, 3). While DL outperforms ML with sufficient data, it is slower and less interpretable. In contrast, ML methods remain valuable for their computational efficiency, relatively simpler parameter tuning, and lower risk of overfitting.

The choice of model architecture significantly influences performance and adaptability across diverse glacial environments. Applying



(a) An example U-Net architecture.



(b) DeepLabv3+ architecture.

Fig. 7. Architectures of key models. Conv, ReLU, and concat stand for convolution, Rectified Linear Unit, and concatenation respectively.

derivatives of U-Net or DeepLab architectures across different study sites is acceptable, as the primary focus is on studying glacial lake dynamics rather than model exploration. However, this approach prioritizes exploitation over exploration, potentially limiting the discovery of novel methods better suited to diverse environmental conditions.

The research community should embrace underexplored architectures, including those successfully applied in other domains of Earth science. For instance, Recurrent Neural Network (RNN)s, including Long Short-Term Memory (LSTM) networks (Sherstinsky, 2020; Hochreiter and Schmidhuber, 1997), are not recent innovations. However, their ability to capture fine-grained time-series dynamics (Ismail Fawaz et al., 2019) remains largely untapped in glacial lake studies. No research has applied these models to analyze temporal lake evolution. Current approaches rely on independent per-image predictions followed by simple multi-temporal analyses. RNNs typically require longer training times than CNNs. However, their potential for recognizing temporal dynamics in glacial lake monitoring warrants further exploration.

A round-robin comparison of the best-performing methods would provide a clearer picture of the trade-offs between computational complexity and performance gains. Including a comprehensive cost–benefit analysis would strengthen this comparison. Together, these efforts could better guide future methodological improvements.

A key challenge is the impact of pre-processing choices, such as atmospheric correction, on performance. Despite its computational cost, the extent to which atmospheric correction improves model accuracy remains largely unquantified. Assessing its effect on classification performance could optimize processing pipelines for large-scale glacial lake studies.

The relevance of ML/DL approaches depends on the application domain. These methods are valuable for regional-scale research where large numbers of lakes need to be analyzed efficiently. However, their utility is limited for site-specific applications – such as hydropower development in discrete or transboundary river basins – where field validation, in situ monitoring, and physically-based hazard modeling are typically required.

6. Conclusion and outlook

Glacial lakes are rapidly expanding due to climate change-driven glacier retreat, increasing the likelihood of outburst floods and impacting human lives and infrastructure. Monitoring these lakes is crucial for assessing hazards, improving early warning systems, and managing freshwater availability. However, effective large-scale studies remain a challenge due to the remoteness of glacial lakes and limited in situ data. Learning-based approaches, particularly deep learning, have emerged as powerful tools, offering numerous opportunities for automating glacial lake mapping and monitoring. However, their full potential remains underexplored.

This paper reviews the existing literature on classical machine learning and deep learning methodologies for remote sensing of glacial lakes. It surveys 48 studies, outlines their respective strengths and weaknesses, identifies key research gaps, and provides best practice recommendations.

Most studies have focused on glacial lakes in Asia, Greenland, and Antarctica. Critical regions such as the Andes and European Alps have received limited attention. Optical sensors, particularly Landsat-8 and Sentinel-2, are widely used, complemented by Sentinel-1 radar data. Optical-only approaches have shown success in polar and mountainous regions but rely heavily on the pre-selection of cloud-free images. Radar-only approaches, on the other hand, have been successful in polar lowlands but are yet to prove effective in mountainous regions. Although radar data mitigates cloud-related issues, it requires extensive pre-processing to be analysis-ready. While both single- and multi-sensor approaches have been explored, multi-sensor fusion – especially SAR-optical combinations – has proven more effective. Despite these advances, mapping and monitoring glacial lakes in mountainous terrain under cloudy conditions remains an unresolved challenge. Furthermore, detecting lakes smaller than 0.01 km^2 remains challenging, primarily due to sensor resolution rather than methodological limitations.

Deep learning methods have demonstrated significant success in glacial lake studies. Convolutional neural networks, particularly U-Net, DeepLab, and their variants, have emerged as prominent approaches. More deep learning approaches have been published compared to classical machine learning and continue to be increasingly reported. Among machine learning methods, random forests and support vector machines have been widely explored. A strong preference for pixel-wise supervised classification is evident. Weakly supervised learning approaches remain underexplored, despite their potential to reduce reliance on extensive ground truth labels. Transfer learning and data augmentation have significantly alleviated the bottleneck of limited labeled data availability. Consequently, training parameter-intensive deep learning models has become more feasible. Nonetheless, high computational costs continue to limit their broader adoption in resource-constrained settings.

To advance robust and scalable glacial lake mapping and monitoring, learning-based approaches must meet several key criteria. High accuracy on primary study sites is essential. Equally important is the ability to generalize across space and time. Ideally, models should adapt to new study regions with minimal retraining. They should also accurately capture intra-annual lake dynamics.

However, several challenges and opportunities remain. Relatively few studies investigate the transferability of their models across study sites and time periods. This raises concerns about generalizability, especially since data-driven approaches are susceptible to overfitting on less representative datasets. Rigorous spatiotemporal transferability experiments with both quantitative and qualitative evaluations must be prioritized.

Moreover, many studies focused on seasonal mapping of glacial lakes rather than year-round monitoring of their temporal evolution. This limits the ability to track intra-annual variations. Future studies should shift focus to multi-temporal analyses. Expanding training datasets with reference data spanning multiple seasons and years is equally important. Additionally, emerging deep learning models capable of learning seasonal and inter-annual variations need to be leveraged to capture dynamic glacial lake evolution.

Existing learning-based approaches, especially deep learning, while effective, operate as black-box models that may violate hydrological and glaciological constraints. Integrating physical principles into data-driven models offers a compelling opportunity to enhance interpretability, explainability and ensure physical consistency. By aligning predictions with known physical behaviors and ensuring physically plausible outputs, unrealistic extrapolations in poorly observed regions can be prevented.

For fair and transparent performance evaluation, future studies should employ robust evaluation metrics that do not overlook class imbalance and stick to standardized benchmarking protocols. High-resolution (spatial) imagery (e.g., PlanetScope, Pléiades, UAV) may be used to improve detection of lakes smaller than 0.01 km^2. However, the associated costs and limited scalability must be considered. Research should be expanded to underrepresented regions. Open-sourcing datasets, ground truth labels, and code could further advance learning-based glacial lake monitoring from space.

CRediT authorship contribution statement

Manu Tom: Writing – review & editing, Writing – original draft, Visualization, Investigation, Conceptualization. **Daniel Odermatt:** Writing – review & editing, Supervision, Project administration, Funding acquisition. **Cédric H. David:** Writing – review & editing, Funding acquisition. **Arnaud Cerbelaud:** Writing – review & editing. **Jeffrey Wade:** Writing – review & editing. **Holger Frey:** Writing – review & editing, Supervision, Project administration, Funding acquisition.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work the lead author used ChatGPT 4o to improve the readability and language of the first draft manuscript. After using this tool/service, all authors reviewed and edited the manuscript and take full responsibility for the content of the publication.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Remote sensing data used

See Table A.3.

[1] http://glofca.org/.
[2] https://alpglacier.geo.uzh.ch/.

Table A.3
Overview of satellite imagery and topographic data used in learning-based glacial lake studies.

Category	Sensor (count)	Publication(s)
Optical satellite imagery	Landsat-8 (22)	Veh et al. (2018), Halberstadt et al. (2020), Yuan et al. (2020), Wu et al. (2020), He et al. (2021), Wang et al. (2021), Thati et al. (2021), Zhao et al. (2021), Chen et al. (2022), Dell et al. (2022), Kaushik et al. (2022), Thati and Ari (2022), Wang et al. (2022a,c), Banerjee and Bhuiyan (2023), Sharma and Prakash (2023), Zhao et al. (2023), Hardie et al. (2024), Sharma et al. (2024), Tang et al. (2024), Wang and Sugiyama (2024) and Xu et al. (2024)
	Sentinel-2 (20)	Dirscherl et al. (2020), Wangchuk and Bolch (2020), Rinzin et al. (2021), Dirscherl et al. (2021), Wendleder et al. (2021), Basit et al. (2022), Chatterjee et al. (2022), Hu et al. (2022), Kaushik et al. (2022), Ortiz et al. (2022), Lutz et al. (2023), Niu et al. (2023), Wei et al. (2023), Xu et al. (2023), Hu et al. (2024), Mustafa et al. (2024), Wang and Sugiyama (2024), Wu et al. (2024), Xu et al. (2024) and Yin et al. (2024)
	Planetscope (5)	Qayyum et al. (2020), Wendleder et al. (2021), Siddique et al. (2023), Thomas et al. (2023) and Xu et al. (2024)
	Landsat-Other (2)	Veh et al. (2018) and Banerjee and Bhuiyan (2023)
	Landsat-7 (1)	Banerjee and Bhuiyan (2023)
	ASTER (1)	Jain et al. (2015)
	Corona KH-4 (1)	Rinzin et al. (2021)
	IRS LISS III (1)	Sharma and Prakash (2023)
Radar satellite imagery	Sentinel-1 (15)	Wangchuk and Bolch (2020), Wu et al. (2020), Zhang et al. (2020b), Dirscherl et al. (2021), How et al. (2021), Rinzin et al. (2021), Wang et al. (2021), Jiang et al. (2022), Kaushik et al. (2022), Wendleder et al. (2021), Xu et al. (2023), Hu et al. (2024), Mustafa et al. (2024), Wu et al. (2024) and Xu et al. (2024)
	TerraSAR-X (1)	Wendleder et al. (2021)
	GaoFen-3 (1)	Chen (2021)
DEM	SRTM (7)	Veh et al. (2018), Wangchuk and Bolch (2020), Rinzin et al. (2021), Wang et al. (2022c), Banerjee and Bhuiyan (2023), Mustafa et al. (2024) and Yin et al. (2024)
	ArcticDEM (5)	How et al. (2021), Hu et al. (2022), Lutz et al. (2023), Wei et al. (2023) and Wang and Sugiyama (2024)
	ASTER (3)	Sharma and Prakash (2023), Hardie et al. (2024) and Sharma et al. (2024)
	ALOS (3)	Veh et al. (2018), Kaushik et al. (2022) and Xu et al. (2023)
	NASADEM (2)	Chen et al. (2022) and Hu et al. (2024)
	TanDEM-X (2)	Dirscherl et al. (2020, 2021)
	Copernicus DEM (1)	Xu et al. (2024)

Appendix B. Search methodology for literature review

To ensure a comprehensive review of glacial lake remote sensing studies that used ML/DL, we conducted a structured literature search using *web of science* and *google scholar*. We included all relevant studies published through the end of 2024 (inclusive).

For *web of science*, we used the search string: [*glacial lakes* OR *glacier lakes*] AND [*deep learning* OR *machine learning*].

In *google scholar*, we used the following keyword combinations: *glacial lakes deep learning, glacial lakes machine learning, glacier lakes deep learning, glacier lakes machine learning, proglacial lakes, ice-dammed lakes, supraglacial lakes, glacial lakes*, and *glacier lakes*.

During the selection process, we first screened titles and abstracts to filter out irrelevant studies. We prioritized peer-reviewed journal articles and conference proceedings. Although *google scholar* offers an extensive search scope, it also returns non-peer-reviewed sources (e.g., preprints), which were excluded. ML/DL papers focusing on general glacier dynamics without addressing glacial lakes were also excluded. Finally, we thoroughly examined the reference lists of short-listed papers to identify any additional relevant studies.

Appendix C. Methodology distribution

See Table C.4.

Appendix D. Variants of U-Net and Deeplab

See Table D.5.

Appendix E. Regional distribution

See Table E.6.

Appendix F. Loss functions and optimization strategies used

See Tables F.7 and F.8.

Appendix G. Glossary

AdaM Adaptive Moment.

AI Artificial Intelligence.

ANN Artificial Neural Network.

ASPP Atrous Spatial Pyramid Pooling.

C-K-MEANS Cascaded K-Means.

CNN Convolutional Neural Network.

CRT Classification and Regression Trees.

DCNN Deep Convolutional Neural Network.

DELSE DEep Level Set Evolution.

DEM Digital Elevation Model.

DL Deep Learning.

EBT Ensemble-Bagged Trees.

FPN Feature Pyramid Network.

GAN Generative Adversarial Network.

GLOF Glacial Lake Outburst Flood.

HMA High Mountain Asia.

IoU Intersection-over-Union.

KNN K-Nearest Neighbors.

Table C.4
Overview of ML and DL methods used for glacial lake remote sensing.

	Methodology [count]	Publication(s)
ML [31]	RF [12]	Veh et al. (2018), Dirscherl et al. (2020), Halberstadt et al. (2020), Wangchuk and Bolch (2020), Rinzin et al. (2021), Wendleder et al. (2021), Chen et al. (2022), Dell et al. (2022), Hu et al. (2022), Banerjee and Bhuiyan (2023), Mustafa et al. (2024) and Wang and Sugiyama (2024)
	SVM [4]	Jain et al. (2015), Halberstadt et al. (2020), Zhang et al. (2020b) and Mustafa et al. (2024)
	K-MEANS+ [3]	
	K-MEANS [2]	Thati et al. (2021) and Wu et al. (2024)
	Cascaded K-Means (C-K-MEANS) [1]	Wu et al. (2024)
	Artificial Neural Network (ANN) [2]	Banerjee and Bhuiyan (2023) and Mustafa et al. (2024)
	Others [10]	
	Logistics Regression (LR) [1]	Mustafa et al. (2024)
	Maximum Entropy (ME) [1]	Halberstadt et al. (2020)
	Naive Bayes (NB) [1]	Halberstadt et al. (2020)
	Classification and Regression Trees (CRT) [1]	Halberstadt et al. (2020)
	Minimum Distance (MD) [1]	Halberstadt et al. (2020)
	Ensemble-Bagged Trees (EBT) [1]	How et al. (2021)
	ISODATA [1]	Thati et al. (2021)
	Learning Vector Quantization (LVQ) [1]	Wu et al. (2024)
	K-Nearest Neighbors (KNN) [1]	Mustafa et al. (2024)
	X-MEANS [1]	Wu et al. (2024)
DL [39]	CNN Variants [37]	
	U-Net [18]	Qayyum et al. (2020), Wu et al. (2020), Chen (2021), Dirscherl et al. (2021), He et al. (2021), Basit et al. (2022), Jiang et al. (2022), Ortiz et al. (2022), Thati and Ari (2022), Wang et al. (2022a), Lutz et al. (2023), Niu et al. (2023), Sharma and Prakash (2023), Siddique et al. (2023), Wei et al. (2023), Hu et al. (2024), Sharma et al. (2024) and Tang et al. (2024)
	DeepLab Variants [6]	Siddique et al. (2023), Xu et al. (2023), Hardie et al. (2024), Sharma et al. (2024), Tang et al. (2024) and Xu et al. (2024)
	CNN [2]	Yuan et al. (2020) and Thomas et al. (2023)
	LinkNet [2]	Thati and Ari (2022) and Cao et al. (2024)
	Others [9]	
	ACFNet [1]	Wang et al. (2021)
	Mask-R-CNN [1]	Chatterjee et al. (2022)
	Feature Pyramid Network (FPN) [1]	Thati and Ari (2022)
	HarDNet (Second-order Attention Network) [1]	Wang et al. (2022c)
	Siamese CNN [1]	Zhao et al. (2023)
	Deep Convolutional Neural Network (DCNN) [1]	Kaushik et al. (2022)
	You Only Look Once (YOLO) [1]	Yin et al. (2024)
	CoAtNet [1]	Xu et al. (2023)
	PSPNet [1]	Thati and Ari (2022)
	Others [2]	
	Generative Adversarial Network (GAN) [1]	Zhao et al. (2021)
	DELSE [1]	Ortiz et al. (2022)

L8 Landsat-8.

LR Logistics Regression.

LVQ Learning Vector Quantization.

MD Minimum Distance.

ME Maximum Entropy.

ML Machine Learning.

MLE Maximum Lake Extent.

MNDWI Modified Normalized Difference Water Index.

NB Naive Bayes.

NDWI Normalized Difference Water Index.

NIR Near InfraRed.

PPC Per-Pixel Classification.

RF Random Forest.

RNN Recurrent Neural Network.

S1 Sentinel-1.

S2 Sentinel-2.

SAR Synthetic Aperture Radar.

SGD Stochastic Gradient Descent.

SVM Support Vector Machine.

SWOT Surface Water and Ocean Topography.

ToA Top of Atmosphere.

UAV Unmanned Aerial Vehicle.

YOLO You Only Look Once.

Data availability

No data was used for the research described in the article.

Table D.5
Different variants of U-Net and DeepLab architectures applied in glacial lake studies. ReLU and FCN stand for Rectified Linear Unit and Fully Convolutional Neural Network, respectively.

Publication	Network	Strategy
Qayyum et al. (2020)	U-Net	Backbones: *VGGNet* (Simonyan and Zisserman, 2015), *EfficientNet* (Tan and Le, 2019)
Wu et al. (2020)		–
Chen (2021)		–
Dirscherl et al. (2021)		Leaky ReLU (Nair and Hinton, 2010; Maas et al., 2013), *ResNet* (He et al., 2016) backbone, dropout (Srivastava et al., 2014), ASPP for multi-scale feature extraction
He et al. (2021)		Self-attention
Basit et al. (2022)		*EfficientNetB0* backbone and *ImageNet* (Deng et al., 2009) pre-trained weights
Jiang et al. (2022)		Attention-based
Ortiz et al. (2022)		Historically guided
Thati and Ari (2022)		GLU-Net with deeper and nested skip connections (He et al., 2016), and pre-processing tailored for remote sensing data
Wang et al. (2022a)		NDWI-attention
Lutz et al. (2023)		Deeper (two extra layers)
Niu et al. (2023)		Attention-based
Sharma and Prakash (2023)		FCN-based (fully convolutional layers) network with *ResNet34* backbone
Siddique et al. (2023)		*EfficientNetB0* backbone
Wei et al. (2023)		–
Hu et al. (2024)		Residual attention [*ResNet50* (He et al., 2016) backbone + convolutional block attention module (Woo et al., 2018)]
Sharma et al. (2024)		*ResNet34* (He et al., 2016) backbone
Tang et al. (2024)		Backbones: *ResNet50*, *Xception* (Chollet, 2017), *MobileNetV2* (Sandler et al., 2018), *MobileNetV3* (Howard et al., 2019)
Siddique et al. (2023)	Deeplab	Deeplab v3+ (Chen et al., 2018b) *MobileNetV2* backbone
Xu et al. (2023)		Panoptic deeplab
Hardie et al. (2024)		Deeplab v3+ with *ResNet18* backbone
Sharma et al. (2024)		Deeplabv3 with *ResNet50* backbone
Tang et al. (2024)		Deeplab v3+ with *ResNet50*, *MobileNetV2*, *MobileNetV3*, *Xception* backbones
Xu et al. (2024)		Deeplab v3+ with *Xception-65* backbone

Table E.6
Regional distribution of traditional and learning-based approaches. ML/DL publications that reported these regions as primary or transferability study sites are shown separately. Within-region transferability sites are not shown.

Region	Notable non-ML publication(s)	ML/DL publication(s) [as primary study site]	ML/DL publication(s) [as transferability study site]
Antarctica	Stokes et al. (2019), Moussavi et al. (2020), Arthur et al. (2020) and Corr et al. (2022)	Dirscherl et al. (2020), Halberstadt et al. (2020), Dirscherl et al. (2021), Dell et al. (2022) and Niu et al. (2023)	–
Greenland	Sundal et al. (2009), Liang et al. (2012) and Carrivick and Tweed (2019)	Yuan et al. (2020), How et al. (2021), Hu et al. (2022), Jiang et al. (2022), Lutz et al. (2023), Wei et al. (2023) and Wang and Sugiyama (2024)	Dirscherl et al. (2021) and Tang et al. (2024)
HMA	Quincey et al. (2007), Bajracharya and Mool (2009), Bolch et al. (2011, 2012), Worni et al. (2013), Wang et al. (2013), Zhang et al. (2015), Allen et al. (2016), Nie et al. (2017), Wang et al. (2020), Ahmed et al. (2021), Chen et al. (2021) and Sajan et al. (2024)	Jain et al. (2015), Veh et al. (2018), Qayyum et al. (2020), Wangchuk and Bolch (2020), Wu et al. (2020), Zhang et al. (2020b), Chen (2021), He et al. (2021), Rinzin et al. (2021), Thati et al. (2021), Wang et al. (2021), Wendleder et al. (2021), Zhao et al. (2021), Basit et al. (2022), Chen et al. (2022), Hu et al. (2022), Kaushik et al. (2022), Ortiz et al. (2022), Thati and Ari (2022), Wang et al. (2022a,c), Banerjee and Bhuiyan (2023), Sharma and Prakash (2023), Siddique et al. (2023), Xu et al. (2023), Zhao et al. (2023), Cao et al. (2024), Hardie et al. (2024), Hu et al. (2024), Mustafa et al. (2024), Sharma et al. (2024), Tang et al. (2024), Wu et al. (2024), Xu et al. (2024) and Yin et al. (2024)	–
Andes	Loriaux and Casassa (2013), Bourgois et al. (2016), Emmer et al. (2016), Cook et al. (2016), Wilson et al. (2018), Emmer et al. (2020) and Veettil and Kamp (2021)	Wangchuk and Bolch (2020)	Qayyum et al. (2020) and Tang et al. (2024)
Canada	Veillette (1994) and Clague and Evans (2000)	–	–
Alaska	Rick et al. (2022)	–	Tang et al. (2024)
Russia	Shugar et al. (2020)	–	–
Scandinavia	Breien et al. (2008) and Andreassen et al. (2022)	–	–
Alps	Huggel et al. (2002), Emmer et al. (2015) and Mölg et al. (2021)	Wangchuk and Bolch (2020)	–
Iceland	Carrivick and Tweed (2019)	–	–
New Zealand	Warren and Kirkbride (1988)	–	–

Table F.7
Overview of loss functions reported.

Loss function (count)	Publication(s)
Cross Entropy (12)	Yuan et al. (2020), Dirscherl et al. (2021), He et al. (2021), Basit et al. (2022), Jiang et al. (2022), Kaushik et al. (2022), Ortiz et al. (2022), Lutz et al. (2023), Xu et al. (2023), Cao et al. (2024), Hardie et al. (2024) and Tang et al. (2024)
Dice (7)	Li et al. (2020), Wang et al. (2021), Thati and Ari (2022), Wang et al. (2022a,c), Cao et al. (2024) and Hu et al. (2024)
Focal (3)	Basit et al. (2022), Siddique et al. (2023) and Thomas et al. (2023)
Tversky (1)	Wu et al. (2020)
Lovasz Hinge (1)	Cao et al. (2024)
Others (4)	Qayyum et al. (2020), Zhao et al. (2021), Basit et al. (2022) and Zhao et al. (2023)

Table F.8
Overview of optimization algorithms reported.

Optimizer (count)	Publication(s)
Adam (15)	Wu et al. (2020), He et al. (2021), Zhao et al. (2021), Basit et al. (2022), Kaushik et al. (2022), Wang et al. (2022c), Lutz et al. (2023), Sharma and Prakash (2023), Siddique et al. (2023), Thomas et al. (2023), Wei et al. (2023), Zhao et al. (2023), Cao et al. (2024), Hardie et al. (2024) and Tang et al. (2024)
SGD (7)	Yuan et al. (2020), Wang et al. (2021), Chatterjee et al. (2022), Ortiz et al. (2022), Thati and Ari (2022), Wang et al. (2022a) and Hu et al. (2024)
AdaMax (1)	Dirscherl et al. (2021)
AdaBelief (1)	Chatterjee et al. (2022)

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