

Spatiotemporal Analysis of Thermokarst-Related Open Water Dynamics and Active Layer Change in the Stordalen Mire

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Bachelor thesis, 15 credits, in Physical Geography and Ecosystem Science

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Abstract

Fennoscandian permafrost peatlands and palsa mires have exhibited pronounced thawing over recent decades, resulting in increased active layer thickness (ALT) and thermokarst formation. Consequently, open water areas have expanded in the well-studied palsa mire Stordalen, located in northernmost Sweden. However, long-term quantifications of open water dynamics remain limited and the relationship between ALT and open water change has received limited attention. Therefore, this thesis investigates spatiotemporal open water dynamics and their relationship to ALT change. Open water areas were identified through manual delineation of historical aerial imagery (1959–2018), combined with Random Forest classification of recent high-resolution imagery (2017–2024). In-situ measurements of ALT, spanning 2010–2018, were incorporated into the analysis. Open water extent increased by 255% in 1959–2018. The number of ponds increased by 429%, although the trend was not linear and therefore not statistically significant. The contemporary analysis showed pronounced interannual variability in both open water extent and pond number. ALT increased significantly between 2010 and 2018, but no significant local relationship between ALT and open water change was found. These findings suggest that thermokarst systems in thawing palsa mires are highly dynamic and that ALT alone does not control local open water development, highlighting the need for continued research of the hydrological processes in thermokarst evolution.

Keywords: thermokarst, peatland permafrost, palsa mire, open water dynamics, active layer thickness, Stordalen, remote sensing

Populärvetenskaplig sammanfattning

I många arktiska miljöer på norra halvklotet har permafrost (mark som är frusen i mer än två år i rad) tinat under de senaste decennierna till följd av den globala uppvärmningen. Eftersom permafrostmarker lagrar stora mängder kol riskerar denna upptining att leda till utsläpp av stora mängder koldioxid och metangas, vilket kan förstärka växthuseffekten. Dessutom påverkar minskningen av permafrost markstabilitet, vegetation och hur vatten rör sig i landskapet. Därför är det viktigt att följa utvecklingen i de miljöer där permafrost finns.

I Skandinavien finns permafrost främst i torvmyrar, där den bildar så kallade palsar. Palsar är frusna torvkullar som höjer sig över de annars ganska flacka myrarna. När permafrosten i palsarna tinar fördjupas det aktiva lagret, det vill säga den delen av marken som tinar årligen varje sommar. Marken kan då sjunka ihop och bilda gropar som fylls med vatten. Dessa grunda vattenansamlingar kallas för termokarstsjöar eller termokarstpölar och är viktiga eftersom de kan producera metangas.

Några kilometer öster om Abisko i Norrbotten ligger palsamyren Stordalen, där forskning bedrivits sedan 1970-talet. Till följd av permafrostsmältning finns här termokarstpölar. Den här studien har kartlagt hur utbredningen av termokarstpölar i Stordalenmyren förändrats från 1959 till 2018 med hjälp av historiska flygfoton. Dessutom analyserades högupplösta drönbilder från 2017 till 2024, för att studera hur mängden öppet vatten varierat under kortare tidsintervall. För att bättre förstå processerna som leder till dessa förändringar analyserades även sambandet mellan djupet av det aktiva lagrets och utvecklingen av termokarstpölar.

Resultaten visar att den yta som täcks av öppet vatten ökat med 255% mellan 1959 och 2018, samtidigt som mängden termokarstpölar ökat kraftigt. Antalet pölar varierad dock mellan olika tidsperioder, vilket gjorde det svårare att bekräfta en långsiktig trend. Det aktiva lagret blev också djupare från 2010 till 2018, vilket tyder på pågående upptining av permafrost. Däremot kunde inget tydligt samband mellan lokala förändringar av det aktiva lagret och uppkomst av termokarstpölar bekräftas. Detta tyder på att det även är andra faktorer som styr var termokarstpölar uppkommer.

Studien visar att termokarstpölar i palsamyrer är väldigt dynamiska, och bör fortsätta studeras, för att kunna förstå och mäta hur förändringarna bidrar till klimatförändringar.

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1 Introduction

Permafrost in Arctic and Subarctic regions has undergone widespread warming and degradation in response to increased global surface temperatures (Biskaborn et al., 2019). In these regions, warming has occurred at a rate 3.8 times faster than the global average between 1979 and 2021 (Rantanen et al., 2022). This phenomenon is called Arctic Amplification.

As permafrost thaws, the thickness of the active layer (AL), the seasonally thawed layer above perennially frozen ground, increases (Hess, 2014). Increasing active layer thickness (ALT) trends have been observed across the Northern Hemisphere (NH) over the past decades (Intergovernmental Panel on Climate Change, 2007; Li et al., 2022) and are projected to persist (Wu et al., 2018). This affects both surface and subsurface processes, influencing ground stability, hydrology, vegetation and the distribution of water in permafrost landscapes (Blume-Werry et al., 2019; Kane et al., 1991; Zastruzny et al., 2023). These alter the soil thermal and moisture conditions, which in turn regulate microbial activity and decomposition of previously frozen organic matter (Chen et al., 2026; Deng et al., 2015). Consequently, the carbon (C) cycle is altered, generally causing increased emissions of greenhouse gases such as carbon dioxide (CO₂) and methane (CH₄) (Dorrepaal et al., 2009; Olefeldt et al., 2012). Permafrost soils currently store 1400–1600 PgC, twice the amount of C found in the atmosphere. Therefore, the thawing of permafrost soils has crucial implications for greenhouse gas emissions (Meredith et al., 2019).

Permafrost thawing and related AL thickening trends have also been reported for the subarctic permafrost peatlands of Fennoscandia (Åkerman & Johansson, 2008; Gislén et al., 2016). This leads to the degradation of peat plateaus and palsas, with subsequent establishment of thermokarst landforms, such as thermokarst lakes, bogs and ponds (Seeman & Sannel, 2024; Thomas et al., 2025; Vasile et al., 2026). As a result, ecological and hydrological changes occur in these landscapes. The vegetation shifts from dry hummock vegetation to wet *Sphagnum* bogs or *Eriophorum* and *Carex* fens (Holmes et al., 2022; Johansson et al., 2006). Further, the anoxic conditions in the increasingly wetter landscapes stimulate CH₄ production and emission (Sjögersten et al., 2022; Turetsky et al., 2020; Varner et al., 2022). The emergence of open water areas, such as thermokarst ponds, is a visual indicator of the described processes (Dixon, 2020). Open water features are relevant in permafrost landscapes, partly as indicators of thermokarst, and partly because of their role in CH₄ emissions from anaerobic decomposition (Anthony et al., 2016). Therefore, there is an urgent need to monitor the areas of open water in permafrost peatlands.

The open water dynamics in permafrost peatlands are spatially heterogeneous and temporally dynamic, due to continuous thaw processes, microtopography and hydrological variability (Zhang et al., 2024). Thus, monitoring long-term changes requires good spatial and temporal data coverage. Due to water's distinct spectral signature, these features can be detected with remote sensing techniques (Günen & Atasever, 2022).

In the permafrost peat mire Stordalen in northern Sweden, permafrost degradation, palsa collapse and vegetation shifts have been monitored over the past decades using both in-situ measurements and remote sensing techniques (Christensen et al., 2004; Johansson et al., 2006; Sjögersten et al., 2023). Changes in open water extent have been reported for 1970–2014 (Christensen et al., 2004; Varner et al., 2022), and more recent thermokarst development has been quantified for 2014–2022 (Thomas et al., 2025). However, existing studies have focused on shorter, specific time periods, rather than conducting a consistent long-term analysis of open water dynamics over several decades. Further, even though both thermokarst development and AL dynamics have been studied in Stordalen, no studies have specifically linked remotely sensed open water changes to measured ALT. To address these gaps, this study combines historical aerial imagery with recent high-resolution data to quantify changes in open water extent and relate these to ALT dynamics.

The aim of this thesis is thus to investigate how thermokarst-related open water dynamics have changed over time in the Stordalen mire and how these changes relate to active layer thickness. Thermokarst development is represented by the spatial and temporal dynamics of open water features, derived from remote sensing data spanning from 1959 to 2024. AL dynamics are represented by in-situ measurements collected across the mire (2010–2018).

Specifically, the research questions are:

1. How did open water extent and the number of ponds change in the Stordalen mire between 1959 and 2018?
2. How did open water extent and the number of ponds change in the Stordalen mire between 2017 and 2024?
3. How are changes in open water extent related to observed active layer thickness?

To address these research questions, this study evaluates the following hypotheses:

- H1.** Open water extent and the number of ponds increased in the Stordalen mire between 1959 and 2018.
- H2.** Open water extent and the number of ponds continued to increase in the Stordalen mire from 2017 to 2024.
- H3.** Increases in open water extent are positively associated with increases in active layer thickness in the mire.

2 Background

2.1 Permafrost and the Active Layer

Permafrost is perennially frozen ground that stays at or below 0 °C for two or more consecutive years (Guo & Wang, 2017). It is found in the polar regions and at high altitudes, with thickness ranging from less than a metre in the southernmost permafrost regions to over 1 km in Siberia (Péwé, 2025). The proportion of the ground in an area constituted of permafrost defines the classification: continuous (>90%), discontinuous (50–90%), sporadic (10–50%) and isolated (<10%) permafrost (Brown et al., 1997). The main controls on permafrost formation and stability are climate, hydrology and surface water, topography and aspect, and geological and soil properties (Smith et al., 2022).

Permafrost generally contains varying amounts of ice. The principal types of permafrost ice are vein ice, pore ice, intrasedimental ice and buried surface ice (Lacelle et al., 2022). Ice content is one of the controls on the nature of permafrost thaw, with ice-rich permafrost losing volume and releasing water (Kokelj & Jorgenson, 2013). This can cause pronounced surface and hydrological changes. In contrast, the thawing of ice-poor permafrost may result in less drastic surface changes (Kokelj & Jorgenson, 2013). Beyond these geomorphological impacts, permafrost thaw also has crucial biogeochemical consequences. Due to the slowing of microbial processes and decomposition of organic material in frozen ground, NH permafrost soils store about twice the amount of C found in the atmosphere, approximately 1460–1600 PgC (Meredith et al., 2019). As permafrost thaws, this previously frozen C becomes available for microbial decomposition and can potentially be released to the atmosphere (Dorrepaal et al., 2009; Dutta et al., 2006).

Where there is permafrost, there is also an AL (Dobiński, 2020). It is defined as the topmost soil layer above permafrost, which experiences seasonal thawing in summer and refreezing in autumn (Hess, 2014). The depth of the AL varies, ranging from a few centimetres in cold regions with continuous permafrost to over a metre in warmer or disturbed regions (Li et al., 2025). It supports roots and microbial activity and is the main biologically active zone in permafrost (Burn, 1998). The AL also governs hydrological connectivity above the permafrost table, as thaw depth influences suprapermafrost water flow and drainage pathways (Walvoord & Kurylyk, 2016).

Trends in increasing ALT have been observed across the NH (IPCC, 2007; Li et al., 2022). This can be attributed to global warming, as ALT is influenced by surface air temperatures (Liu, 2023). However, as ALT also depends on soil type, snow and vegetation cover, organic layer thickness and soil moisture, the response to climate warming is differential (Peng et al., 2023). Increased ALT causes several shifts in both surface and subsurface processes. Firstly, it alters ground stability, which can lead to infrastructure damage and landslides (Patton et al., 2021; von Deimling, 2021). Secondly, increased ALT influences the hydrological cycle, shifting drainage patterns and groundwater flows, and affecting chemical water transport (Olefeldt et al., 2012). Further, the C cycle in permafrost soils is altered, as the increased ALT stimulates microbial decomposition of organic matter (Chen et al., 2026). This generally leads to CO₂ and

CH₄ release from previously frozen organic matter (Christensen et al., 2004; Dorrepaal et al., 2009; Knoblauch et al., 2021), although responses are differential depending on local vegetation, as well as hydrological and microbial properties (Keuschnig et al., 2022).

2.2 Fennoscandian Peatland Permafrost Mires and Palsas

In the Fennoscandian Subarctic, permafrost is mainly found in peatland mires (Gisnås et al., 2016). Peat is essential for permafrost formation in these regions, due to its insulating properties (Seppälä, 2006). In summer, the dry peat acts as an insulator, keeping the soil cool even as the air temperature rises. Contrastingly, in winter, the wet peat has higher thermal conductivity, allowing the cold air to penetrate into the soil. Peatlands form in waterlogged areas where anoxic conditions and cool temperatures inhibit decomposition, leading to accumulation of partially decomposed plant matter (Craft, 2022). The vegetation that forms peat mainly consists of *Sphagnum* and other mosses, *Carex*, *Eriophorum* and other sedge vegetation, as well as ericaceous shrubs (Sannel et al., 2017). As much of this organic matter is frozen, decomposition rates are strongly reduced. Therefore, vast amounts of C are stored in permafrost peatlands, approximately 185 PgC (Hugelius et al., 2020). As previously outlined, this C constitutes a major potential C release to the atmosphere following permafrost thaw.

A common formation in these landscapes are palsas. They are elevated peat mounds with a frozen core of ice (Seppälä, 2006). Palsas can have varying morphology, with areas ranging from a few square metres for dome-shaped palsas to palsa plateaus covering a km² (Åhman, 1977; Seppälä, 2006). Their height ranges from 0.5 to 7 m, with palsa plateaus reaching a height of 1–1.5 m (Seppälä, 2006). Palsa mires have varying microtopography. This heterogeneity is reflected in the hydrological conditions, featuring dry hummocks and wet hollows. These palsa mires are, according to the EU's habitat directive, a “key habitat”, a classification that entails conservation of them (Janssen et al., 2016).

Palsa formation requires distinct hydrological and thermal conditions (Seppälä, 2006). In Fennoscandia, they are mainly found in regions with mean annual air temperature (MAT) ranging from -5 to -3 °C and annual precipitation not exceeding 450 mm (Luoto et al., 2004). Palsas form due to ice lens accumulation in the peat or silt sediments (Seppälä, 2006). This process is triggered by freezing from above, when wind action decreases snow cover locally (Seppälä, 2006). Eventually, palsas reach a mature state, after which they begin to degrade and form thermokarst (Seppälä, 2006).

Widespread palsa degradation has been observed across Fennoscandia (Verdonen et al., 2023). In Sweden, this has caused subsidence in more than 55% of palsa peatlands (Valman et al., 2024) and in Finland, an overall decrease of 63–76% has been observed since the 1960s (Leppiniemi et al., 2025). As these palsa mires are located at the southern edge of the permafrost zone, they are particularly vulnerable to even small changes in temperature and precipitation (Olvmo et al., 2020; Seppälä, 2010), both of which are predicted to increase with climate change (Lind et al., 2022). As dry peat insulates from increased summer air temperatures, precipitation is the main issue (Seppälä, 2010). Increased summer precipitation causes wetter peat, thereby decreasing its insulating capacities. In winter, increased precipitation causes thicker snow

cover, leading to warmer soils (Seppälä, 1990). Together, these processes can decrease permafrost stability and accelerate palsa degradation.

2.3 Thermokarst in Palsas

A consequence of palsa degradation is the abovementioned thermokarst formation (Seppälä, 2006). Thermokarst refers to the landforms and processes resulting from the thawing of ice-rich permafrost and ensuing ground subsidence (Kokelj & Jorgenson, 2013). Subsequently, water input leads to the formation of thermokarst ponds or lakes. In palsa mires, thermokarst occurs due to thawing of the ice core within the palsa, consequently leading to surface subsidence (Seppälä, 2006). As outlined in 2.2, this is a natural part of the cyclic development of palsas (Seppälä, 2006). However, due to climate change, with increased temperatures and/or precipitation, palsa degradation and thermokarst formation are accelerating, potentially exceeding the rate of new palsa formation (Borge et al., 2017; Thomas, 2025; Verdonen et al., 2023). This leads to hydrological changes, such as altered drainage patterns, wetter landscapes, and pond or fen expansion (Olefeldt et al., 2021).

The transition from palsa to thermokarst also initiates vegetation shifts, with dry hummock vegetation transitioning to *Sphagnum* bogs or *Eriophorum* and *Carex* fens (Holmes et al., 2022; Johansson et al., 2006). Over time, some thermokarst ponds may gradually transition into vegetated wetlands through vegetation infilling (Jabłońska et al., 2025; Olefeldt et al., 2021). Further, the increasingly wetter landscape constitutes a positive feedback loop. Water has a lower albedo and higher heat capacity than the surrounding palsa, which in turn increases the speed of permafrost thaw (Harris, 2002). Therefore, open water can be considered both a consequence and a driver of thermokarst development.

Water inputs that contribute to thermokarst ponds can include precipitation, both direct rainfall and snowmelt runoff, suprapermfrost water that flows in the AL, meltwater from thawing permafrost and lateral inflow from the surrounding areas (Fig. 1; Somera et al., 2025). The suprapermfrost water is hydrologically connected to the surrounding surfaces and is strongly controlled by AL depth (Qin et al., 2024; Woo, 2011). Lateral flow in the mire occurs through saturated peat, controlled by its hydraulic conductivity (Fewster et al., 2023). There are also outputs from thermokarst ponds. These include evaporation and drainage or outflow to connected ponds or streams via surface and subsurface flow (Olefeldt et al., 2021; Somera et al., 2025).

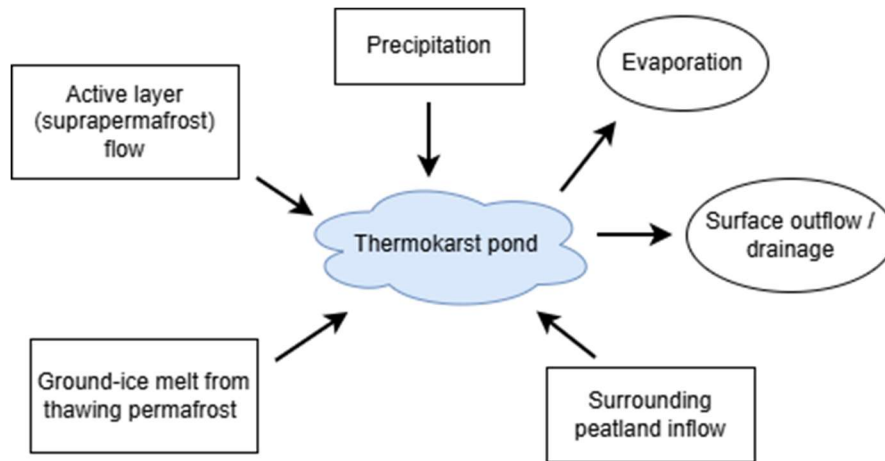


Figure 1. A conceptual model showing water inputs to (represented by squared boxes) and outputs from (represented by ovals) thermokarst ponds. The arrows indicate whether the water contributes to the pond (pointing toward the pond) or is removed from the pond (pointing away from the pond).

These processes favour both organic matter decomposition and CO₂ release from the thawed peat. Varner et al. (2022) found comparatively higher emissions of CO₂ from open water areas than other landcover types in Stordalen. Further, due to anaerobic decomposition in the wet thermokarst areas, there is also substantial CH₄ release (Johansson et al., 2006; Varner et al., 2022). As CH₄ is a very potent greenhouse gas, monitoring thermokarst processes is crucial (Shirley et al., 2025; Varner et al., 2022).

2.4 Remote Sensing of Thermokarst and Surface Water

Thermokarst development can be monitored in the field (Jabłońska et al., 2025) or using remote sensing techniques (Lu et al., 2025; Thomas et al., 2025). For this, imagery of different spatial resolutions can be used. In permafrost research, commonly used formats include satellite imagery such as Sentinel-2 data (Freitas et al., 2019; Karlson & Bastviken, 2023) or historical aerial orthophotos (Borge et al., 2017; Olvmo et al., 2020; Seemann & Sannel, 2024). Also, high-resolution imagery captured by unmanned aerial vehicles (UAVs) is widely used (Valman et al., 2024; Vasile et al., 2026).

While there are several thermokarst landforms, such as thermokarst bogs, ponds and lakes (Vasile et al., 2026), open water features like ponds and small lakes represent a distinct and observable stage of thermokarst development. Due to the strong spectral contrast with surrounding vegetation, these constitute a good proxy for mapping thermokarst extent with remotely sensed data. Moreover, open water features are comparatively easy to detect in imagery of varying spatial and spectral resolution.

In remote sensing, topographical and spectral indices and/or variables are often used. Topographical variables are mainly derived from digital elevation models (DEMs), which represent the Earth's surface (Guth et al., 2021). Slope has been found to be one of the most important factors for identifying thermokarst (Wang et al., 2023). Further, a slope raster can be used to derive flow direction and flow accumulation, using flow model algorithms (Esri, n.d.; O'Callaghan & Mark, 1984). In turn, flow accumulation and slope are used together to calculate a Topographic Wetness Index (TWI, Eq. 1), as first formulated by Beven & Kirkby (1979).

TWI has previously been found to show a strong correlation to the land cover in Stordalen (Persson et al., 2012) and has been associated with thermokarst occurrence (Krutskikh et al., 2023; Wang et al., 2023).

$$TWI = \ln\left(\frac{FlowAcc + 1}{Tan(SlopeRad)}\right) \quad (\text{Equation 1})$$

Several spectral bands are relevant for water detection. In the near-infrared (NIR) band, water has very low reflectance, while vegetation exhibits high reflection (Lillesand, 2015). As water is generally spectrally distinct from wet vegetation in the NIR spectrum, this band is highly useful for this study (Özesmi & Bauer, 2014). Further, it can be used to derive the Normalised Difference Water Index (NDWI; McFeeters, 1996; Eq. 2) and the Normalised Difference Vegetation Index (NDVI; Tucker, 1979; Eq. 3).

$$NDWI = \frac{Green - NIR}{Green + NIR} \quad (\text{Equation 2})$$

$$NDVI = \frac{Red - NIR}{Red + NIR} \quad (\text{Equation 3})$$

NDWI is widely used to detect surface water (Özelkan, 2020), whereas NDVI enables separation between vegetated and non-vegetated surfaces (Özesmi and Bauer, 2002). Using both indices facilitates separation of water from wet, vegetated areas, which can be challenging in transitional permafrost peatlands (Thomas et al., 2025). This is a practice commonly applied in remote sensing studies of wetlands (Ashok et al., 2021; Zhao et al., 2026). Finally, the red-edge band can be used to significantly improve classification of densely vegetated wetlands, as it enhances sensitivity to vegetation properties (Kaplan & Avdan, 2019).

2.5 Spatiotemporal Change Detection and Random Forest Classification

Spatiotemporal change detection is important for remote sensing analyses of surface changes. The nature of the data is one of the determinants of the quality of the output. For a long-term change analysis, a long temporal cover is necessary, while for rapid changes in landscapes with high short-term variability, dense temporal cover is needed. There is often a trade-off between sufficient temporal and spatial resolution. Combining historical aerial imagery with recent UAV imagery can therefore enable both long-term and high-resolution analysis of thermokarst development (Verdonen et al., 2023).

There are different methodological approaches to change detection. These are mainly manual digitisation or automated classification. Manual digitisation is generally regarded as time-consuming and entails subjectivity depending on the digitiser. Automated classification methods, on the other hand, favour reproducibility and efficiency compared to manual approaches, especially when large datasets are analysed (Maxwell et al., 2018).

Further, there are several automated and semi-automated classification approaches for high-resolution imagery. In this study, Random Forest (RF) classification is used. RF is an ensemble method that builds multiple decision trees (Breiman, 2001). The decision trees are based on

labelled training data. To train each tree, the model creates subsets of the original data (bootstrap sampling) and at each split, a random subset of predictors is used. This reduces variance and overfitting and increases the robustness of the model (Breiman, 2001). Moreover, it can handle a large number of variables and non-linear relationships and is therefore suitable for remote sensing (Belgiu & Drăguț, 2016). RF is a commonly used approach in thermokarst detection studies (Lu & Han, 2025) and has demonstrated strong performance over other machine learning methods in several studies (Janiec et al., 2023; Kartoziia, 2025; Wang et al., 2023). In Stordalen, RF has been used for soil organic carbon mapping, also outperforming other models (Siewert, 2018).

3 Methods

3.1 Site Description

The Stordalen mire is located at 68.20°N, 19.03°E, about 10 km east of Abisko Scientific Research Station, within the subarctic region of northern Sweden, close to the Scandinavian mountain range (Fig. 2). The area belongs to the discontinuous permafrost zone (Holmes et al., 2022). The climate is subarctic, with long, cold winters and short, cool summers (ICOS Sweden, 2022). Stordalen is situated in one of the driest regions of Sweden, due to rain shadow from the nearby mountain range, with average annual accumulated precipitation of 332 mm yr⁻¹ (1981–2010) and average annual air temperature of -0.1°C (1981–2010) (ICOS, 2022). Stordalen is a well-studied peatland mire, with extensive research conducted on the site since the early 1970s (Climate Impacts Research Centre, n.d.), especially in relation to permafrost thaw and carbon cycling (Christensen et al., 2004; Ström & Christensen, 2007; Svensson, 1974).

The mire is situated at 351 m.a.s.l and is a relatively flat landscape with small-scale topographical variability. It is a peatland complex, underlain by discontinuous permafrost, with ALT varying seasonally (Lupascu et al., 2018) and increasing in response to recent warming (Åkerman & Johansson, 2008; Johansson et al., 2006). The landscape is a mosaic of elevated palsas, partially degraded due to permafrost thaw (de la Barreda-Bautista et al., 2022; Thomas et al., 2025). The thawed subsidence areas exhibit wetter conditions and thermokarst features such as thermokarst bogs, shallow thermokarst lakes and ponds, and thaw sinks (de la Barreda-Bautista et al., 2022; Vasile et al., 2026). The area has a water table that exhibits spatial and seasonal variability (Persson et al., 2012). This landscape and hydrological heterogeneity is also reflected in the vegetation in the area. Peat bogs and sedge/*Eriophorum* wetlands dominate the site, together with smaller areas of *Sphagnum* wetlands, forested wetlands and alpine heath tundra (Siewert, 2018). Significant land cover changes have been observed since the 1970s (Varner et al., 2022), partly driven by permafrost degradation (Christensen et al., 2004; Johansson et al., 2006).

As seen in Fig. 2, there are two study areas used for the open water analysis. The larger study area was defined using a 20 m buffer around the AL measurement points. However, the contemporary UAV imagery does not cover this full extent. Thus, a smaller study area was applied for this data, limited to the smallest UAV extent (2017). The full extent was used for the long-term analysis (1959–2018), and the UAV extent was used for the short-term analysis (2017–2024).

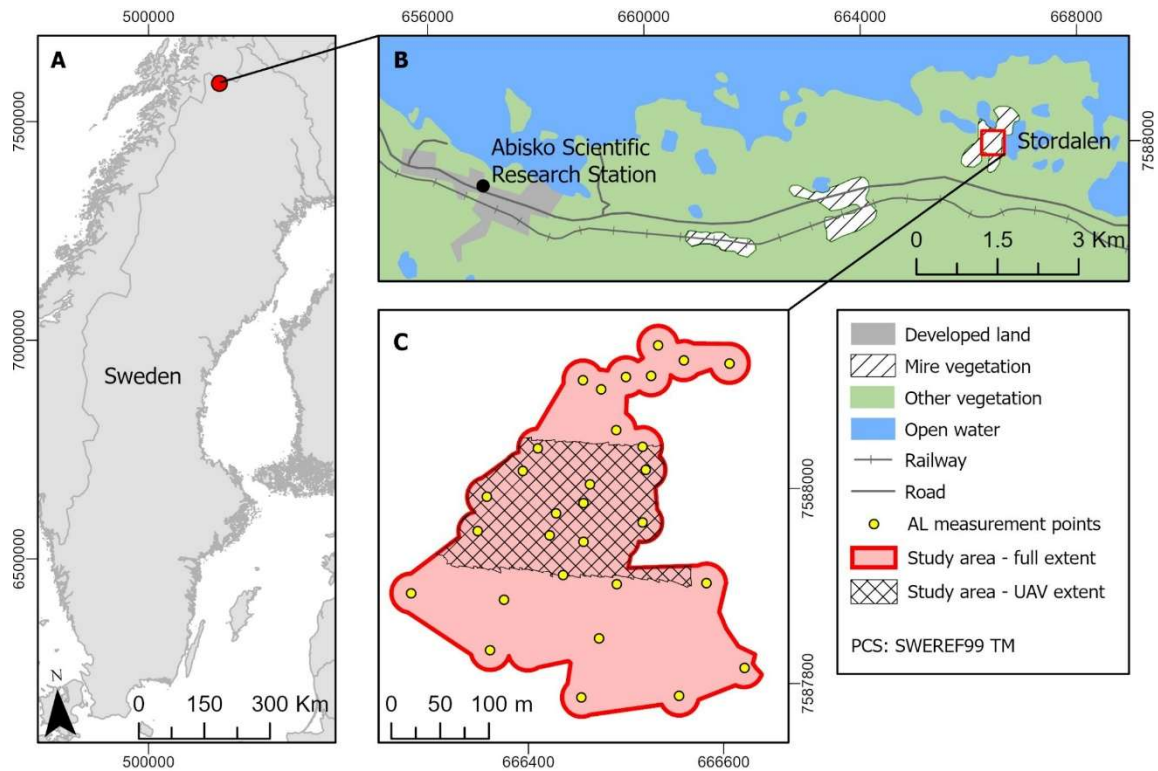


Figure 2. Maps showing A) the location of the study area in Sweden and B) the location of the study site in relation to Abisko Scientific Research Station, as well as the nearby surroundings, with land cover data sourced from the Swedish National Land Survey's vegetation map for the Norrbotten region (Lantmäteriet Vegetationskartan Norrbotten). C) shows the study area used for the long-term analysis (1959–2018) in red and pink, the smaller study area used for the UAV analysis (2017–2024) delineated with a grid and the AL measurement points marked with yellow dots.

3.2 Data

3.2.1 Imagery

To analyse recent open water dynamics in the study area, very high resolution (2.5–5 cm) orthomosaics and DEMs recorded with UAVs were obtained for the years 2017, 2018, 2019 and 2024 (Table 1). For the years 2017–2019, the spectral bands were constituted of red (R), green (G), near infrared (NIR) and red edge (RE). For 2024, the spectral bands were R, G and blue (B).

Table 1. Datasets used for the analysis of recent open water dynamics in the smaller study area, including UAV-derived orthomosaics and DEMs from 2017 to 2024.

Date	Data type	Bands	Resolution	Source
2017-07-04	UAV orthomosaic	R, G, NIR, RE	2.5 cm	Olsson, P-O (2017).
2017-07-04	DEM	Elevation	5 cm	Olsson, P-O (2017).
2018-07-31	UAV orthomosaic	R, G, NIR, RE	5 cm	Olsson, P-O (2018).
2018-07-31	DEM	Elevation	5 cm	Olsson, P-O (2018).
2019-08-13	UAV orthomosaic	R, G, NIR, RE	5 cm	Olsson, P-O (2019).
2024-06-12	UAV orthomosaic	R, G, B	5 cm	Abisko Scientific Research Station (2025)
2024-06-12	DEM	Elevation	5 cm	Abisko Scientific Research Station (2025)

To analyse long-term spatiotemporal open water changes, aerial orthophotos were downloaded from the Swedish National Land Survey (Lantmäteriet), covering a temporal extent of 59 years (1959–2018) (Fig. 3, Table 2). The orthophotos had spatial resolutions of 0.5–1 m and were panchromatic or true colour (RGB).

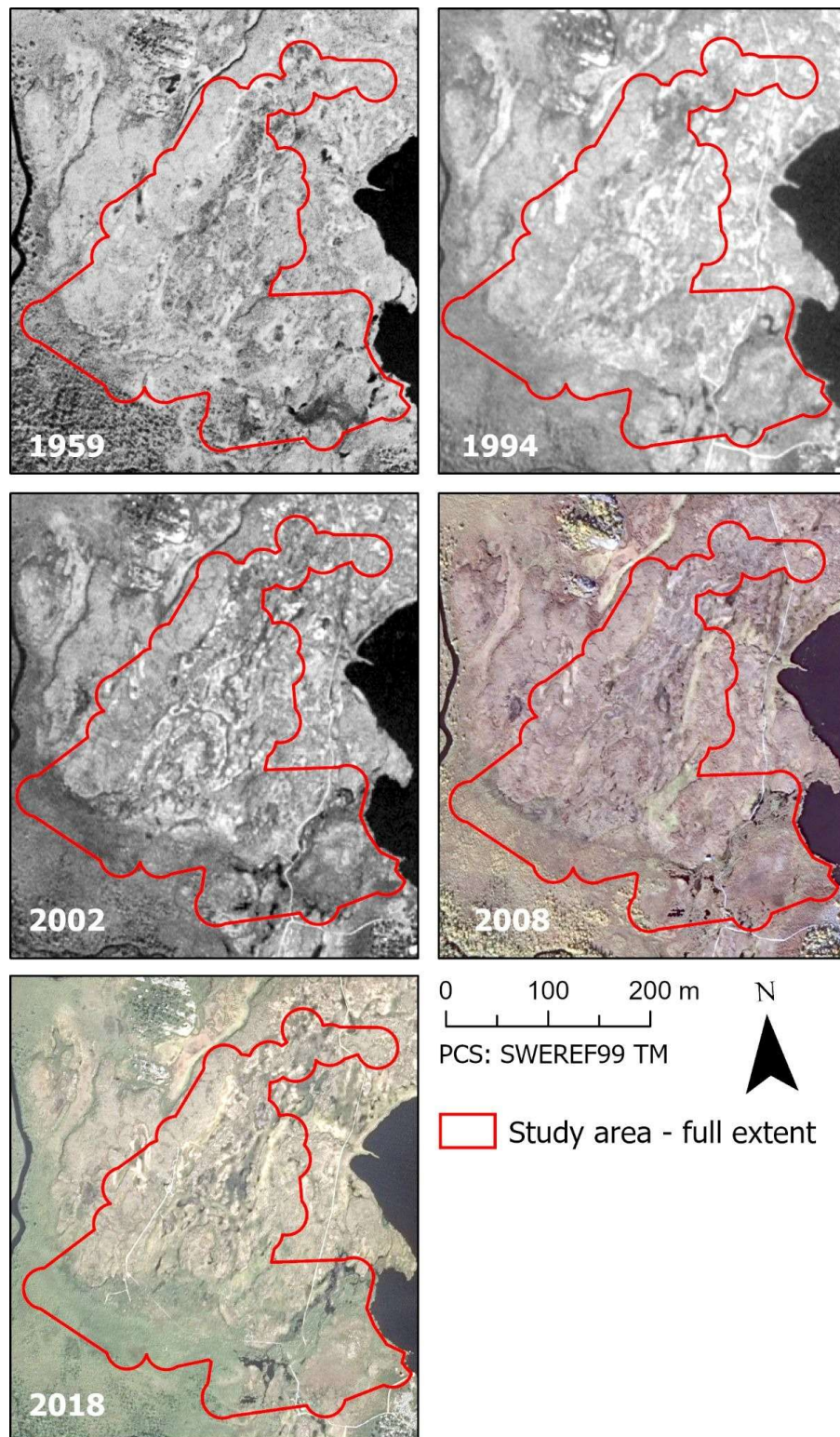


Figure 3. Orthophotos of the Stordalen mire in 1959, 1994, 2002, 2008 and 2018. The red line in each image indicates the full extent of the study area. All orthophotos are sourced from the Swedish National Land Survey (Lantmäteriet).

Table 2. Datasets used for the long-term analysis of open water areas, including panchromatic and RGB orthophotos.

Date	Data type	Resolution	Source
1959-08-02	Orthophoto, panchromatic	0.5 m	Lantmäteriet, image number 758_66_55_1960
1994-09-02	Orthophoto, panchromatic	1 m	Lantmäteriet, image number 758_66_55_1994
2002-08-05	Orthophoto, panchromatic	1 m	Lantmäteriet, image number 758_66_55_2002
2008-09-10	Orthophoto; R, G, B	0.5 m	Lantmäteriet, image number 758_66_55_2008
2018-07-28	Orthophoto; R, G, B	0.5 m	Lantmäteriet, image number 758_66_55_2018

3.2.2 Active Layer Measurements

To relate open water changes to AL dynamics in the area, in-situ ALT measurements for 2010, 2017 and 2018 were provided by Andreas Persson. The set up of these measurements is described in Persson et al. (2012). The data consisted of 30 point measurements (Fig. 2), divided into three peatland classes: palsa bog, internal fen and fen. At the time of establishment of the measurements, the palsa bog was underlain by permafrost, the internal fen area featured the collapsing, thawing palsa, and the fen area was permafrost-free (Persson et al., 2012). At each location, measurements were taken hourly by an automatic sensor.

Continuous AL measurements (1978–2023) for other permafrost sites in the Abisko region were obtained from Åkerman (1998, updated). The locations were composed of 9 valley (mire) and 3 mountain sites. Only data for the valley sites were used in the present study.

3.2.3 Climate Data

To relate open water and ALT dynamics to climate change, historical data on mean monthly temperature and total monthly precipitation were downloaded from the Swedish Meteorological and Hydrological Institute (SMHI, n.d.) for the whole study period (1959–2024). Annual averages of temperature and cumulative precipitation were derived and split into intervals corresponding to the time ranges between the historical imagery (Table 2) as well as a final interval to cover the recent years (2018–2024) (Table 1). This interval-based approach was inspired by Wallin (2025).

Additionally, to survey if recent short-term dynamics in open water extent relate to climatic variability, temperature and precipitation anomalies were calculated for the summer months (JJA) for the years 2017–2024. These anomalies represent deviations from the 30-year means (1991–2020) for each month respectively.

3.3 Classification of UAV Imagery

To survey recent changes in open water extent, very high-resolution UAV orthomosaics were used for the years 2017, 2018, 2019 and 2024 (Table 1). Corresponding DEMs were used for the years 2017, 2018 and 2024. For 2019, as no DEM was available, the 2018 DEM was used, assuming no drastic terrain changes in the span of one year. The workflow consisted of (1) pre-processing and predictor variable generation, (2) supervised RF classification and (3) accuracy assessment, post-processing and feature extraction. All steps were performed in ArcGIS Pro (version 2.7.3, Esri Inc., Redlands, USA).

3.3.1 Pre-processing and Predictor Variables

The analyses were performed with cell size and snap raster set to the original DEM of the respective years, to ensure consistent rasters for the classifications. Slope and TWI were derived from the DEMs, using the D8 method to calculate flow direction (Fig. 4). The calculation for TWI was adopted from Beven & Kirkby (1979), with an additional 0.001 added to the denominator, to avoid division by 0 in the areas of 0 slope (Eq. 4).

$$TWI = Ln\left(\frac{FlowAcc + 1}{Tan(SlopeRad) + 0.001}\right) \quad (\text{Equation 4})$$

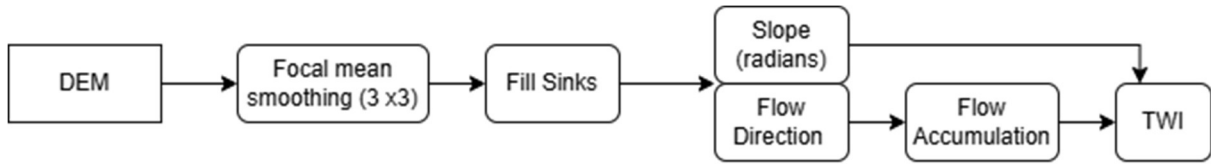


Figure 4. Flowchart showing the DEM preprocessing workflow conducted in ArcGIS Pro to create the layers to be used for the open water classification. Input layers are presented in squares, and ArcGIS layers and outputs in rounded rectangles.

NDWI and NDVI were computed for each year where NIR bands were available (2017–2019), using the raster calculator tool (Eqs. 2 and 3).

Finally, composite rasters with all predictor variables were created for each year, using the tool composite bands. Topographic variables, including slope and TWI, were used for all years. For 2024, all available spectral bands were used (RGB, Fig. 5A). For the multispectral datasets (2017–2019), spectral predictor variables included NDWI and NDVI, as well as the NIR and red-edge bands (Fig. 5B). The red and green bands were excluded from the composite rasters to reduce redundancy, since they are represented within the indices.

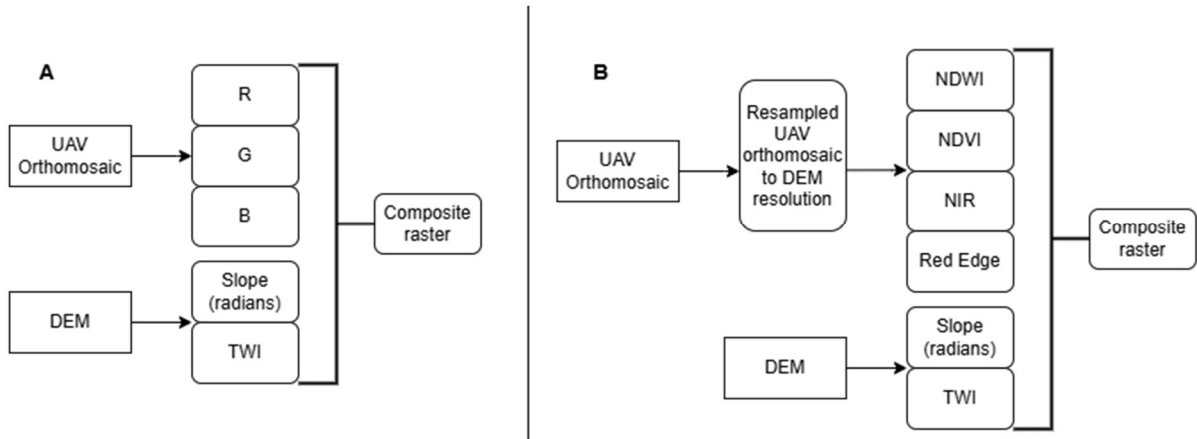


Figure 5. Flowchart showing the creation of composite rasters with all predictor variables for the image classification for A) 2024 and B) 2017–2019. Input layers are presented in squares, and ArcGIS layers and outputs in rounded rectangles.

3.3.2 Random Forest Classification

To classify the open water areas in the 2017–2024 UAV imagery, the supervised machine learning algorithm RF was conducted in ArcGIS Pro (version 2.3.7), for the years 2017–2024, respectively. Two classes were defined: “Open Water” and “Other”. The class Open Water was defined as clearly delineated, continuous water bodies with a smooth texture and no apparent surface vegetation, with high NDWI values, low NDVI values and located in areas of low slope and high TWI. These features represent the open water stages of thermokarst systems and are visually distinct from the surrounding land cover. All other land cover classes, including waterlogged *Sphagnum* or sedge wetlands were assigned to the class “Other”.

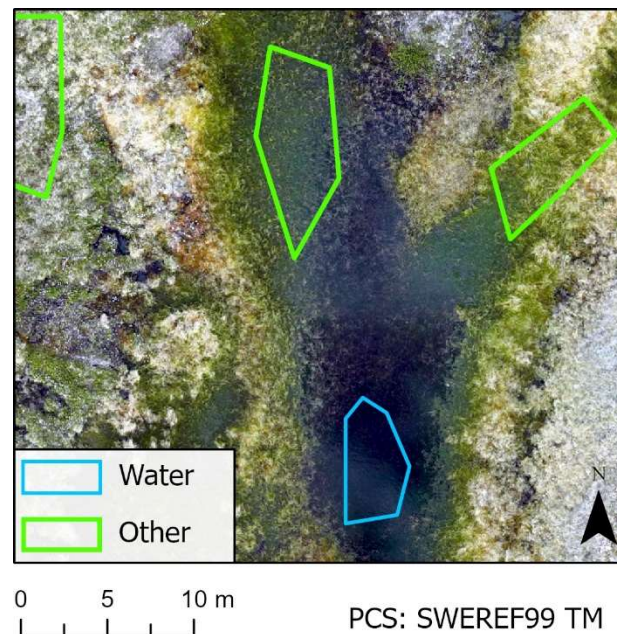


Figure 6. Example image of training polygons created for the Random Forest classification, with polygons of the class Water shown in light blue and Other in light green. The background image is a UAV-derived orthomosaic (RGB) captured on 2024-06-12 (Abisko Scientific Research Station, 2025).

The imagery was divided into two subsets by a west-east transect, with the northern half used as a training area and the southern half reserved for validation. Training polygons representing

the classes “Open Water” and “Other” were manually delineated, with 30 polygons of each class, visually ensuring an even spatial distribution across the training area. Only distinct pond cores with smooth texture and no visible vegetation were delineated as open water (Fig. 6). A mapping scale of 1:200 was used to ensure consistent interpretation of the high-resolution imagery. This scale was chosen to balance the high spatial resolution (5 cm) with practical delineation. The composite raster generated during pre-processing (Fig. 5) was then used with the training data to train the RF model (Fig. 7). The number of trees was set to 100, since previous classification studies have shown that errors stabilise around this value (Mellor et al., 2013). Subsequently, the trained model was used to classify the whole study area. This process was repeated independently for each year (2017–2024).



Figure 7. Flowchart showing the RF classification steps conducted in ArcGIS Pro. ArcGIS layers and outputs are represented by rounded rectangles, and ArcGIS tools are represented by ovals.

3.3.3 Accuracy Assessment, Post-processing and Feature Extraction

An overview of the post-processing and feature extraction is seen in Fig. 8. Following classification, a majority filter (8 neighbourhoods) was applied to reduce speckle in the classified raster, following Thomas (2025). 100 accuracy assessment points were generated within the validation subset, using equalised stratified random sampling. The points were validated using visual inspection of the original UAV imagery and predictor variable rasters. A consistent mapping scale of 1:200 was applied. Finally, a confusion matrix was computed using the ArcGIS Pro tool, and kappa values and accuracy measure were extracted.

The classified raster was subsequently reclassified by assigning all “Other” pixels as “NoData”. The tool “Region Group” (8 neighbourhood) was applied to aggregate adjacent features. Then, the raster was converted to a polygon layer. A minimum mapping unit (MMU) was applied to remove small features unlikely to constitute stable thermokarst water bodies, such as water patches in inundated wetland. Thresholds of 1, 2 and 5 m² were evaluated. An MMU of 1 m² resulted in noise from inclusion of inundated wetland and a highly skewed feature size distribution. A threshold of 5 m² resulted in over-smoothing and exclusion of smaller but relevant thermokarst features. Thus, an MMU of 2 m² was selected as a balance, and all polygons below this limit were excluded.

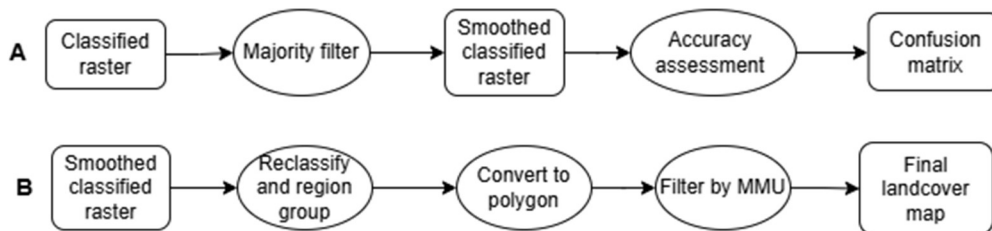


Figure 8. Flowchart outlining A) the method for accuracy assessment and B) post-processing and feature extraction in ArcGIS Pro. ArcGIS layers and outputs are represented by rounded rectangles, and ArcGIS tools are represented by ovals.

3.4 Manual Delineation of Orthophotos

For the long-term spatiotemporal open water analysis, manual digitising of orthophotos (Fig. 3, Table 2) was applied. This approach was chosen due to the lower spatial resolutions and fewer spectral bands available, compared to the UAV imagery, and the absence of DEMs before 2017. The predictor variables used for the RF classification could therefore not be consistently derived for the orthophotos, making automated classification less suitable. The same land cover class definitions as defined in 2.3.2 were used.

In a thermokarst mapping report, a minimum mapping scale (MMS) of 1:20 000 was used for imagery with a spatial resolution of 10 m (Gibson et al., 2020). This scale was used as a reference for adapting the MMS to the higher resolution imagery in the present study, to ensure consistent interpretation across datasets with disparate resolutions. Accordingly, MMS of 1:1000 was used for the 0.5 m resolution orthophotos and 1:2000 for the 1 m resolution orthophotos.

The most recent imagery (2018) was digitised first, using the high-resolution UAV imagery from the same year to help distinguish open water features. Colour, texture and shape were used to delineate the open water features. The imagery was digitised successively, working backwards in time. A conservative approach was applied to dark areas with speckled texture, likely representing wet *Sphagnum* or sedge wetlands, to avoid overestimation of open water extent. The same MMU of 2 m² as for the UAV imagery was used. Figure 9 shows examples of manually digitised open water polygons.

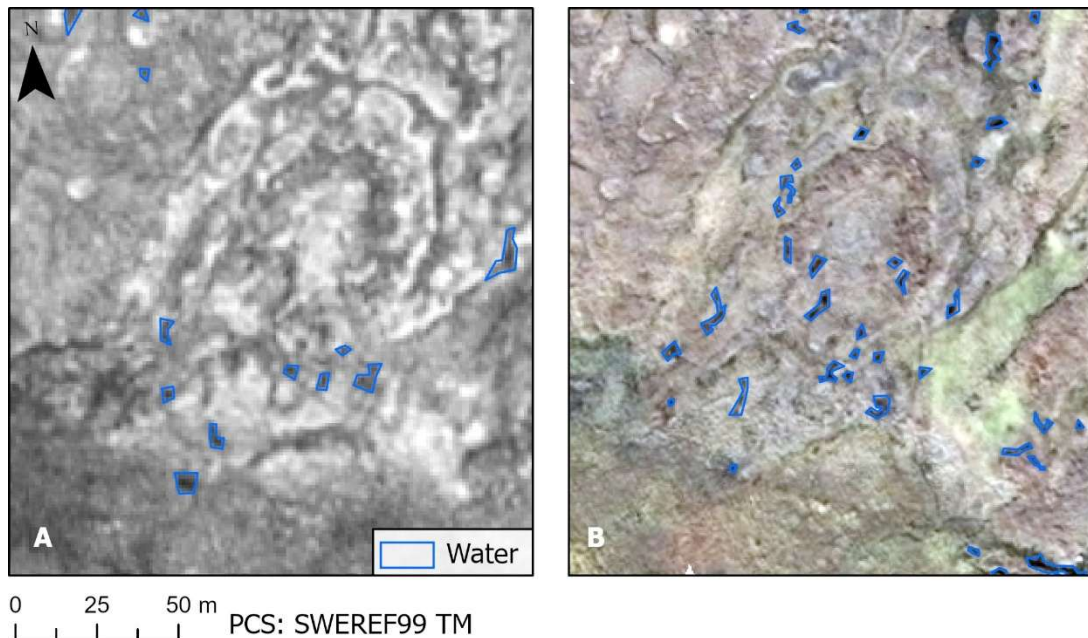


Figure 9. Examples of manually digitised open water polygons in orthophotos from A) 2002 (panchromatic) and B) 2008 (RGB). Both orthophotos are sourced from the Swedish National Land Survey (Lantmäteriet), with image numbers 758_66_55_2002 (A) and 758_66_55_2008 (B).

Finally, an accuracy assessment was conducted using the same method and number of accuracy assessment points as for the UAV imagery, outlined under 3.3.3.

3.5 Statistical Analyses of Open Water Change

Statistical analyses of open water dynamics were conducted in RStudio (version 2024.04.0). Separate analyses were performed for the short-term (2017–2024) and the long-term (1959–2018) datasets. For both temporal spans, linear regression models were used to evaluate trends in total open water area, number of ponds, as well as mean and median pond area. For the long-term analysis, MMUs of 2 m² and 10 m² were used to conduct two separate analyses. This was done to account for differences in image resolution and with consideration to the absence of water bodies <10 m² in the 1994 imagery.

For all linear regression analyses, the assumptions of linear regression were evaluated using diagnostic plots and Shapiro-Wilk tests of the residuals (Rogerson, 2010). For total open water area in the long-term analysis, the assumption of normality was not met (Shapiro-Wilk test, $p < 0.05$). A linear model was thus used to evaluate the trend, and p -values were not considered. For the short-term analysis, a non-monotonic trend was seen for both open water area and the number of ponds. Further, the assumptions of linear regression were partly violated. Therefore, the results were treated descriptively.

3.6 Active Layer Dynamics

3.6.1 Active Layer Dynamics by Peatland Type

To survey how changes in ALT over time (2010–2018), the maximum ALT (using the maximum measured value in the period 22 June – 10 September) values for each peatland class were analysed in RStudio. A linear mixed effects model was applied to survey the variation in ALT over time and between land cover classes, using the R packages lme4 and lmerTest (Kuznetsova et al., 2017). This test was chosen as the measurements were taken from the same points across all years and were thus not independent. Estimated marginal means were calculated to interpret significant effects and interactions. Then, pairwise Tukey's tests were performed to identify differences between groups. For this, the emmeans package was used (Lenth & Piaskowski, 2026).

3.6.2 Analysis of ALT and Open Water Change (2008–2018)

To relate changes in open water extent (2008–2018) to AL dynamics, maximum seasonal (22 June – 10 September, measured hourly) ALT values were derived for 2010 and 2018 for the measured points. ALT data was compiled in a point layer in ArcGIS, with attribute fields for each year. For each point, the change in ALT between 2010 and 2018 was calculated. Points with missing ALT values for one or both years were excluded from change calculations. Then, circular buffer zones ($r = 10$ m) were created around each point, to extract local open water extent. This buffer was intersected with mapped open water polygons for 2008 and 2018, described under 3.4. For each buffer, open water presence and extent were calculated for 2008 and 2018, respectively. Finally, the change in open water extent (2008–2018) was calculated within each buffer. A sensitivity analysis using a 20 m buffer was also conducted. However, this resulted in overlapping buffers and was therefore not used for any further analysis. This workflow is outlined in Fig. 10.

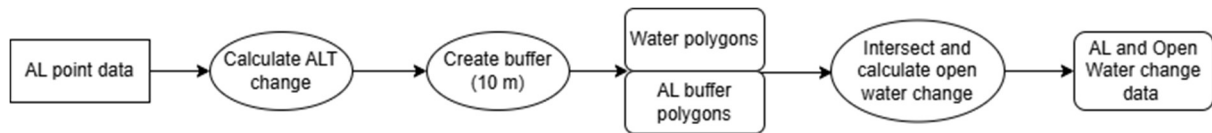


Figure 10. Flowchart outlining the method for the ALT and open water change analysis in ArcGIS.

Subsequently, statistics were calculated for ALT change in RStudio. A linear regression analysis was conducted to test the relationship between ALT change and open water change. To survey if the assumptions of linear regression were met, linearity, homoscedasticity and normality of residuals were visually evaluated. Finally, a t-test was performed to test whether the change in ALT differed between points with and without open water presence.

3.6.3 Regional Active Layer Trends Across Abisko Mire Sites

To relate the findings of this study to regional ALT trends, mean ALT data for 9 other Abisko mires (Åkerman, 1998, updated) was used. The relationship between ALT and time was tested using linear regression in RStudio. The assumptions of linear regression were tested and visually evaluated.

4 Results

4.1 Long-Term Changes in Open Water Extent (1959–2018)

Under an MMU of 2 m², the total number of ponds increased by 429% during the study period (1959–2018) (Fig. 11, Table 3). The total open water area increased by 255%. Contrasting the long-term trends, a decrease in the number of ponds was seen between 1959 and 1994. In 1994, the number of ponds had decreased by approximately 52%. The mean and median pond area were notably higher in 1994, compared to the other years. 1994 also features the highest standard deviation, indicating marked areal difference between features.

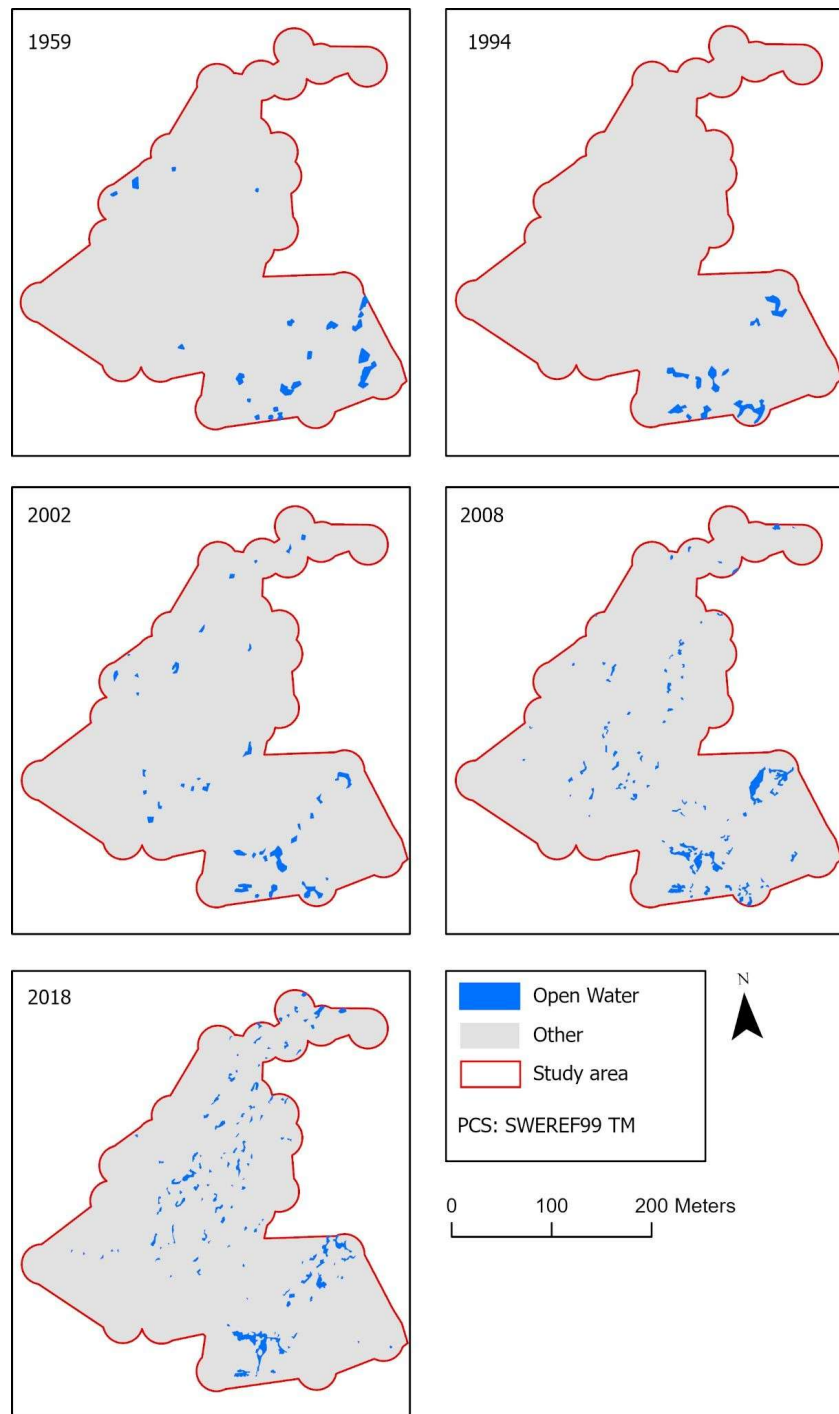


Figure 11. Manually digitised open water extent in the larger study area in 1959, 1994, 2002, 2008 and 2018 (MMU = 2 m²). Open water areas are shown in blue and all other land cover types in grey.

Table 3. Open water statistics (number of ponds and area metrics) derived from orthophoto classifications for 1959–2018 (MMU = 2 m²).

Year	Number of ponds	Total area (m²)	Mean area (m²)	Median area (m²)	St. dev area (m²)
1959	21	592	28.2	16.9	29.1
1994	10	1066	106.6	91.4	79.2
2002	35	1253	35.8	20.1	39.8
2008	86	1845	21.5	9.2	33.5
2018	111	2099	18.9	9.4	44.2

Applying an MMU of 10 m², the total number of ponds increased by 333% during the study period (Table 4). The total open water area increased by 243%. Here, the number of ponds decreased by 17% between 1959 and 1994. The mean and median pond areas were notably higher for 1994 compared to the other surveyed years, however, the difference was less pronounced than for the MMU of 2 m².

Table 4. Open water statistics (number of ponds and area metrics) derived from orthophoto classifications for 1959–2018 (MMU 10 m²).

Year	Number of ponds	Total area (m²)	Mean area (m²)	Median area (m²)	St. dev area (m²)
1959	12	525	43.8	36.9	30.2
1994	10	1066	106.6	91.4	79.2
2002	30	1218	40.6	22.9	41.1
2008	42	1585	37.7	23.5	42.3
2018	52	1801	34.6	19.8	61.0

Using an MMU of 2 m², a strong increase in open water area was observed over time (Fig. 12A; $R^2 = 0.85$). On average, the total open water area increased by 24.8 m² yr⁻¹. A similar trend was observed under the stricter MMU of 10 m², with a pronounced increase in open water areas over time (Fig. 12B; $R^2 = 0.94$) and an average increase of 21.2 m² yr⁻¹. The greatest rate of change is seen between 2002 and 2008, with an average change of +100 m² yr⁻¹ under an MMU of 2 m² and +61 m² yr⁻¹ for an MMU of 10 m².

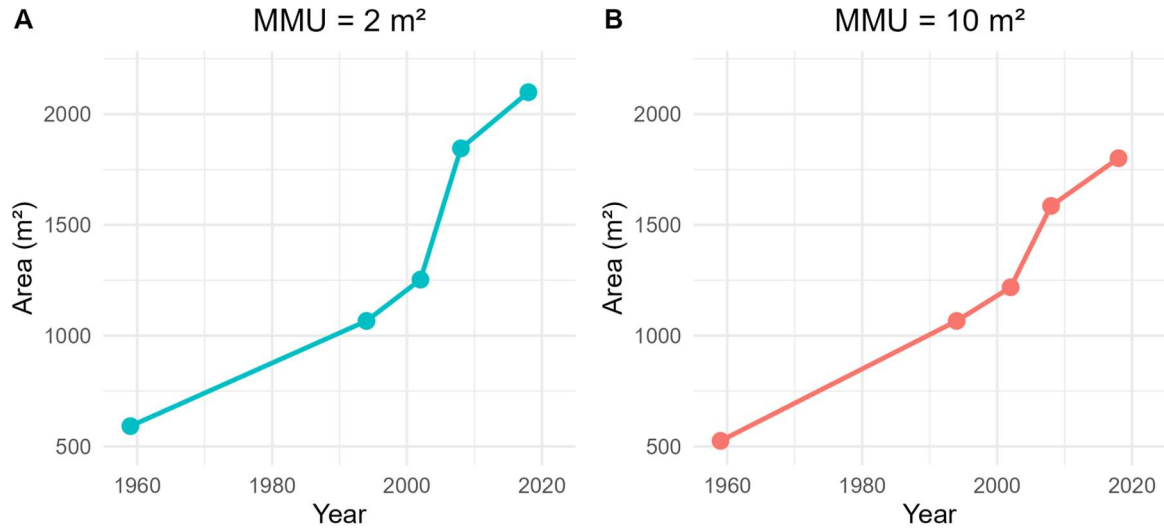


Figure 12. Graphs showing total open water area over time during the study period (1959–2018). The relationship is shown for A) MMU = 2 m² and B) MMU = 10 m². Values are derived from manual interpretation of historical orthophotos.

With an MMU of 2 m², the number of ponds showed a positive but non-significant increase of +1.39 ponds yr⁻¹ ($R^2 = 0.52$, $p > 0.05$; Fig. 13A). An increase of +0.66 ponds yr⁻¹ was also seen under an MMU of 10 m² ($R^2 = 0.65$, $p > 0.05$; Fig. 13B).

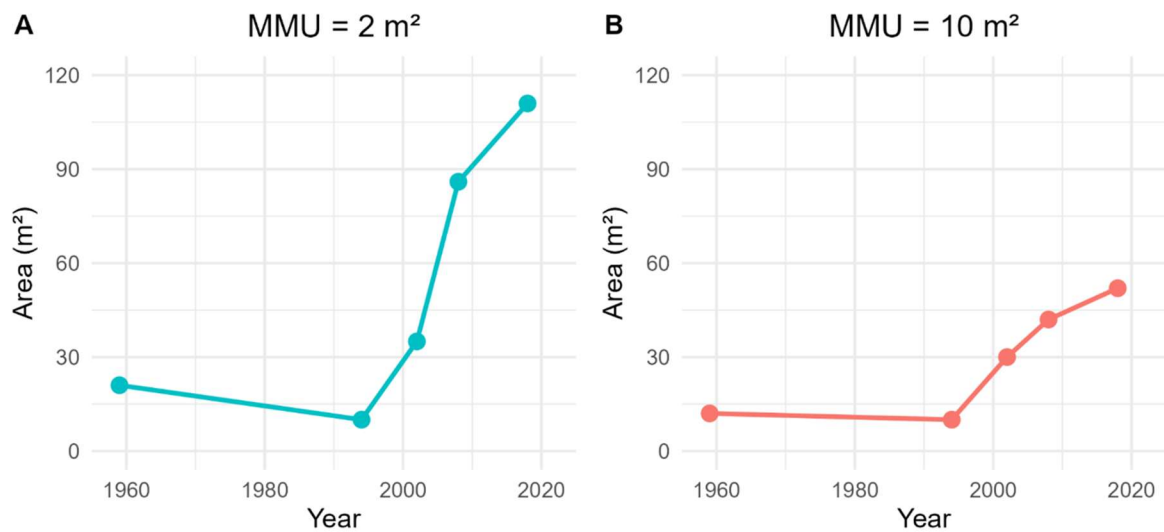


Figure 13. Graphs showing number of ponds over time during the study period (1959–2018) for A) MMU = 2 m² and B) MMU = 10 m². Values are derived from manual interpretation of historical orthophotos.

No temporal trend was observed in pond size metrics for either MMU (Tables 3 and 4). For MMU = 2 m², both mean and median pond areas showed no significant relationships with time ($R^2 = 0.015 - 0.016$, $p > 0.5$). Similarly, for MMU = 10 m², mean ($R^2 = 0.024$, $p > 0.05$) and median pond area ($R^2 = 0.072$, $p > 0.05$) showed no significant relationship with time.

4.2 Short-Term Changes in Open Water Extent (2017–2024)

The total area and number of open water features varied substantially between the years (Fig. 14, Table 5). The number of ponds decreased from 115 in 2017 to a minimum of 24 ponds in 2019, subsequently increasing again to 84 features by 2024 (Fig. 15B). The total area of open water features followed a similar trend, with a maximum of 1076 m² in 2017, a minimum of 96 m² in 2019 and a recovery to 790 m² by 2024 (Fig. 15A). The mean pond size was relatively stable across 2017, 2018 and 2024 (8.5–9.4 m²), but notably smaller in 2019 (4.0 m²). Median pond size exhibited less variation (5.3–5.4), indicating a left-skewed distribution in pond size in 2017, 2018 and 2024. This is also seen in the relatively high standard deviations, especially in 2017 and 2024. The smallest standard deviation in pond size was observed in 2019.

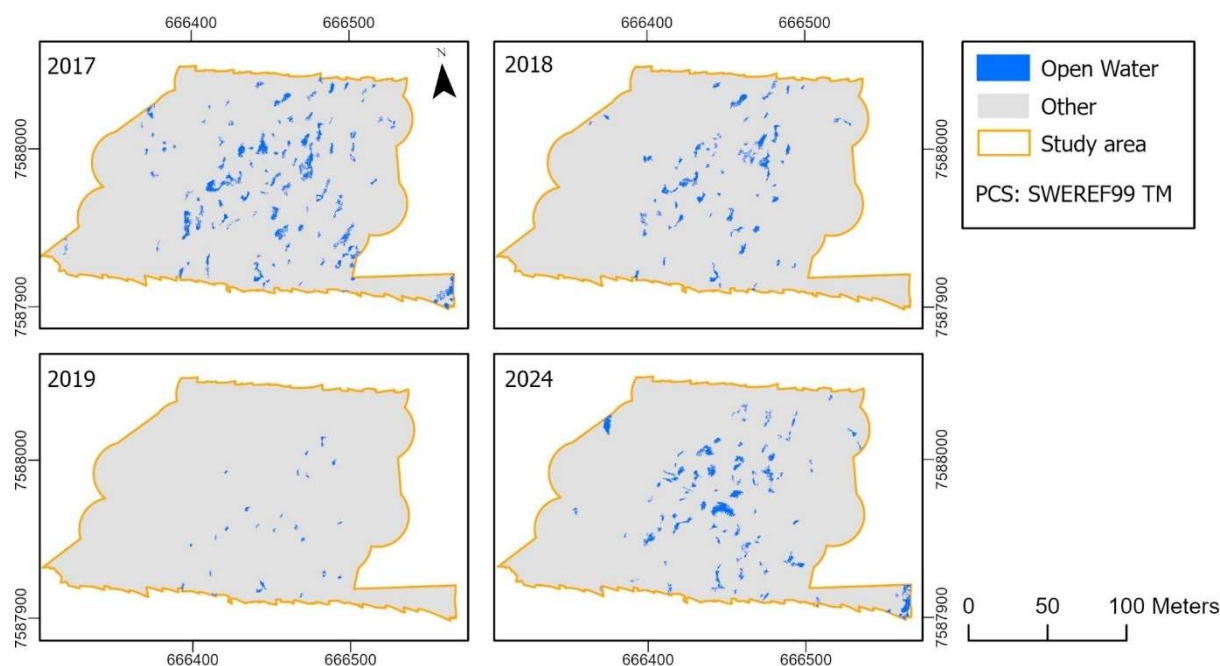


Figure 14. Spatial distribution of open water in the smaller study area, derived from Random Forest classification of UAV imagery from 2017, 2018, 2019 and 2024. Open water areas are shown in blue and all other land cover types in grey.

Table 5. Open water statistics (number of ponds and area metrics) derived from Random Forest classification of UAV imagery from 2017–2024 (MMU = 2 m²).

Year	Number of ponds	Total area (m ²)	Mean area (m ²)	Median area (m ²)	St. dev area (m ²)
2017	115	1076	9.4	5.4	11.7
2018	64	544	8.5	5.3	8.7
2019	24	96	4.0	3.3	1.7
2024	84	790	9.4	5.1	12.6

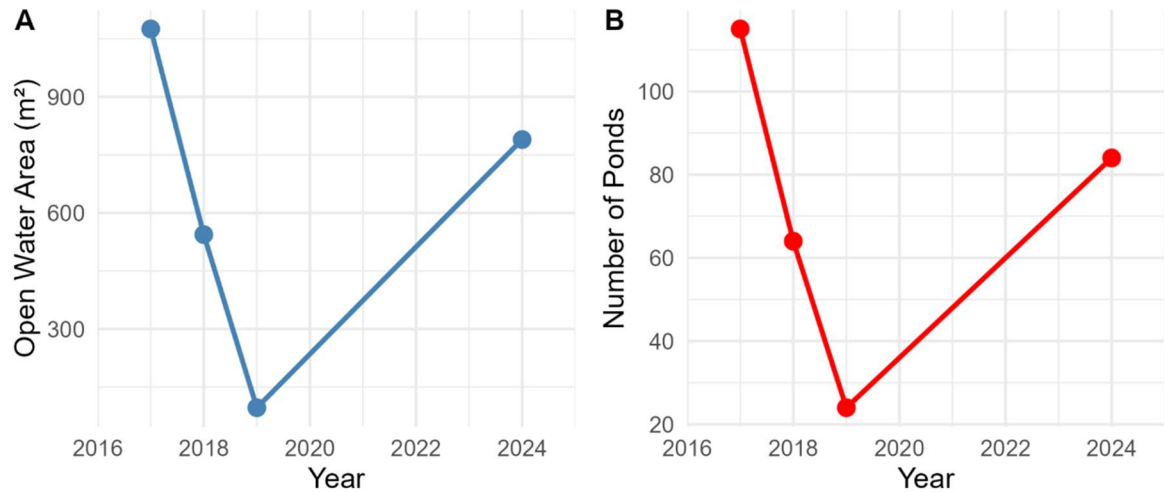


Figure 15. Temporal change in A) total open water extent (m²) and B) number of ponds in the smaller study area 2017–2024. Values are derived from Random Forest classification of UAV imagery for 2017–2024, using an MMU of 2 m².

4.3 Accuracy Assessment of the Open Water Classifications

Accuracy assessments of both the manual classification and the RF classification are presented in Tables 6 and 7. The RF classifications achieved overall accuracies of 84.5–89% and the manually digitised classifications achieved overall accuracies of 90–94%.

Table 6. Output of the accuracy assessment of the Random Forest classification. For each year, respectively, overall accuracy (%) and kappa value, as well as Producer's (P) and User's (U) accuracies for the classes Open Water and Other are reported.

Year	Overall accuracy %	Kappa	P accuracy - Open Water (%)	U accuracy - Open Water (%)	P accuracy - Other (%)	U accuracy - Other (%)
2017	84.5	0.69	1	68.1	76.9	1
2018	87.9	0.76	1	75.5	80.6	1
2019	89.0	0.78	1	78.0	82.0	1
2024	84.7	0.70	1	70.0	76.2	1

Table 7. Output of the accuracy assessment of the manual digitisation. For each year, respectively, overall accuracy (%) and kappa value, as well as Producer's (P) and User's (U) accuracies for the classes Open Water and Other are reported.

Year	Overall accuracy %	Kappa	P accuracy - Open Water (%)	U accuracy - Open Water (%)	P accuracy - Other (%)	U accuracy - Other (%)
1959	92	0.84	0.98	0.87	0.87	0.98
1994	90	0.80	0.98	0.82	0.84	0.98
2002	94	0.88	0.98	0.90	0.91	0.98
2008	94	0.88	0.98	0.90	0.91	0.98
2018	94	0.88	0.96	0.92	0.93	0.96

4.4 Active Layer Dynamics

4.4.1 Active Layer Dynamics by Peatland Type

Mean maximum ALT in the study area increased from 2010 to 2018, for all peatland types (Fig. 16). The linear mixed effects model showed that time had a significant effect on ALT over the period 2010–2018 ($n = 26$; $F = 19.21$; $p < 0.001$) and that peatland type also had a significant effect ($n_{\text{palsa bog}} = 10$; $n_{\text{internal fen}} = 10$; $n_{\text{fen}} = 6$; $F = 6.21$; $p = 0.007$). The interaction effect between time and peatland type was, however, not statistically significant ($F = 0.33$, $p > 0.05$), which indicates that the trends over time were similar for all peatland types. The post-hoc analyses revealed a significant increase in ALT between 2010 and 2018 ($p < 0.001$), as well as between 2017 and 2018 ($p < 0.001$). No significant difference was observed between 2010 and 2017 ($p > 0.05$). Among peatland types, ALT differed significantly between palsa bogs and fens ($p = 0.007$), but no significant differences were found between internal fens and either palsa bogs or fens ($p > 0.05$).

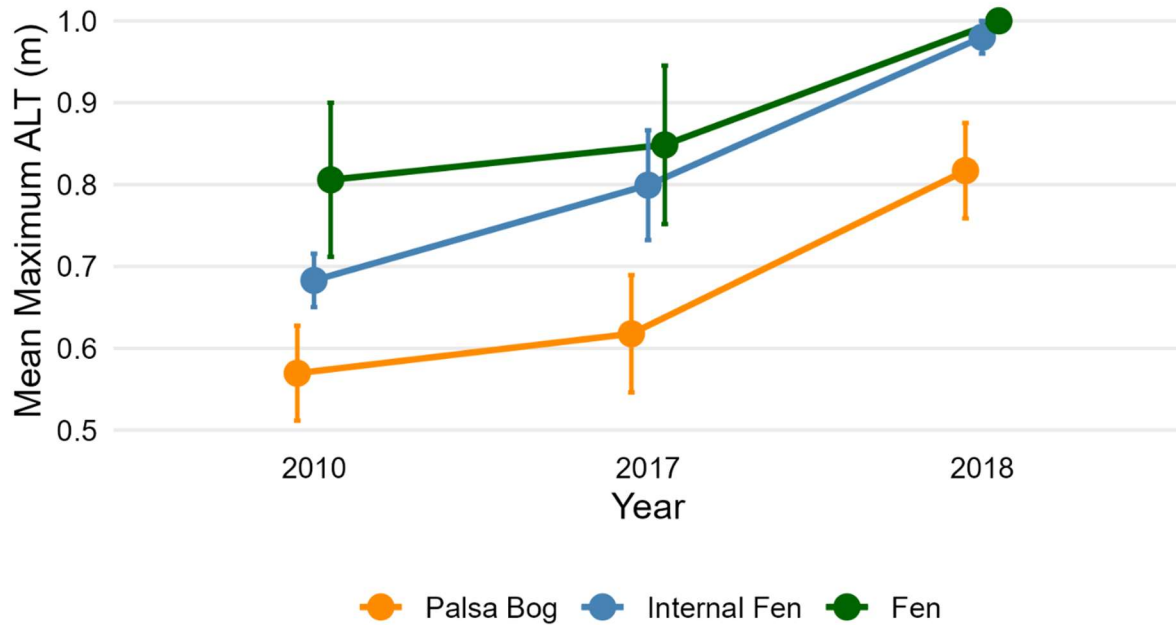


Figure 16. Mean maximum ALT (m) over time (2010–2018) for the peatland types Palsa Bog (orange, $n = 10$), Internal Fen (blue, $n = 10$) and Fen (green, $n = 6$). Error bars represent standard deviations.

4.4.2 ALT and Open Water Change Dynamics (2008-2018)

Maximum ALT exhibited a general increase in the study area from 2010 to 2018, with a mean increase of 0.25 m (median = 0.2 m) (Table 8). Changes in ALT ranged from 0 m to +0.68 m. Changes in open water extent within the buffer zones varied between -37.5 m² and +71.2 m², while 50% of the points showed no change in water extent between 2008 and 2018.

Table 8. Descriptive statistics for ALT change (m; 2010–2018; $n = 26$) and open water change (m²; 2008–2018).

Variable	Mean	Median	Min	Max	St. dev
ALT change (m)	0.25	0.27	0	0.68	0.18
Water change (m ²)	5.7	0.0	-37.5	71.2	18.3

The linear regression analysis revealed no statistically significant relationship between changes in ALT and open water extent ($R^2 = 0.02$, $p > 0.05$), indicating that increases in ALT were not associated with increases in open water area (Fig. 17).

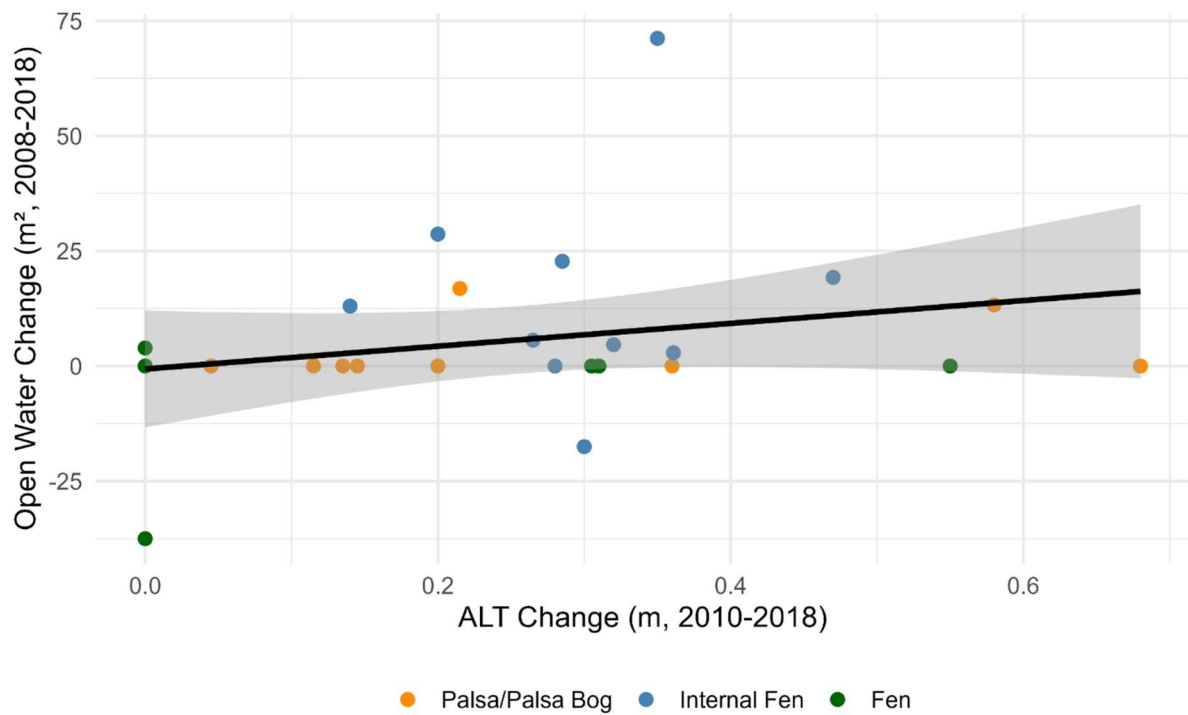


Figure 17. Linear regression between open water change (m²; 2008–2018) versus ALT change (m; 2010–2018; $n = 26$). Data points represent palsa bog (orange, $n = 10$), internal fen (blue, $n = 10$) and fen (Green, $n = 6$). The grey shading indicates the confidence interval.

ALT measurement points associated with open water did not exhibit a statistically significantly higher ALT (mean = 0.29 m) compared to points without open water (mean = 0.23 m) (Fig. 18; $p > 0.05$).

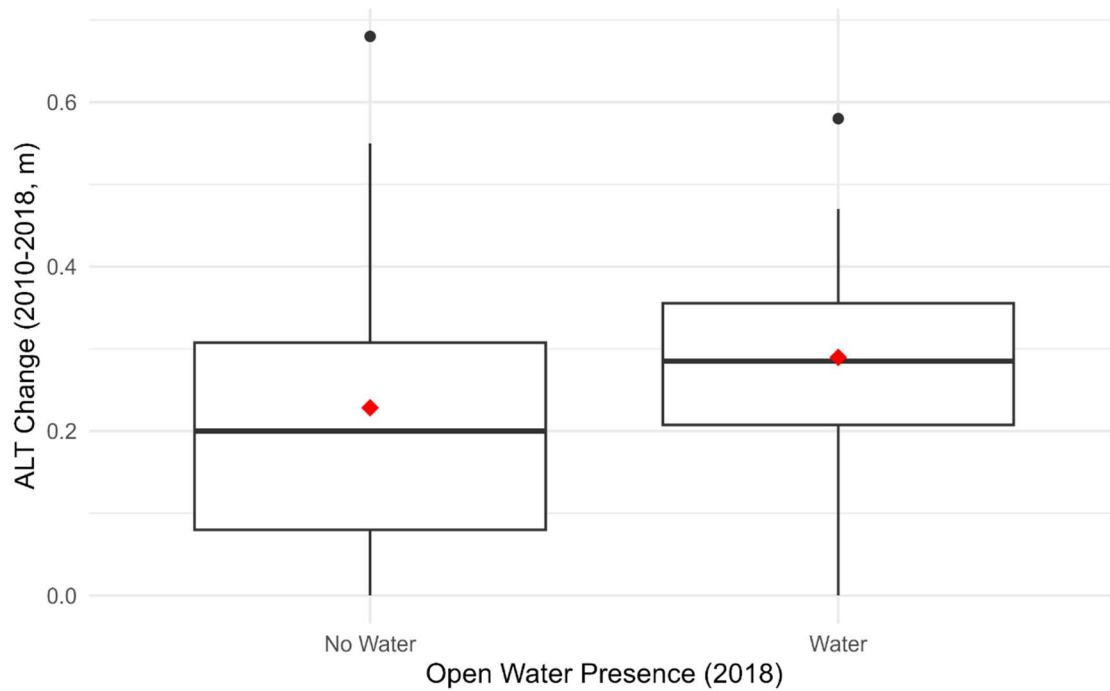


Figure 18. Boxplots of observed ALT change from 2010 to 2018 (mm) for points with no open water presence (No Water, $n = 15$) versus open water presence (Water, $n = 11$) (2018). For each group, the mean is indicated by a red diamond and the median by a thick black line.

Increases were observed in both ALT and open water extent during the analysed periods (Fig. 19). Mean maximum ALT increased by 0.02 m yr^{-1} from 2010–2018 (Fig. 19A), while open water extent increased by $25.3 \text{ m}^2 \text{ yr}^{-1}$ from 2008–2018 (Fig 19B).

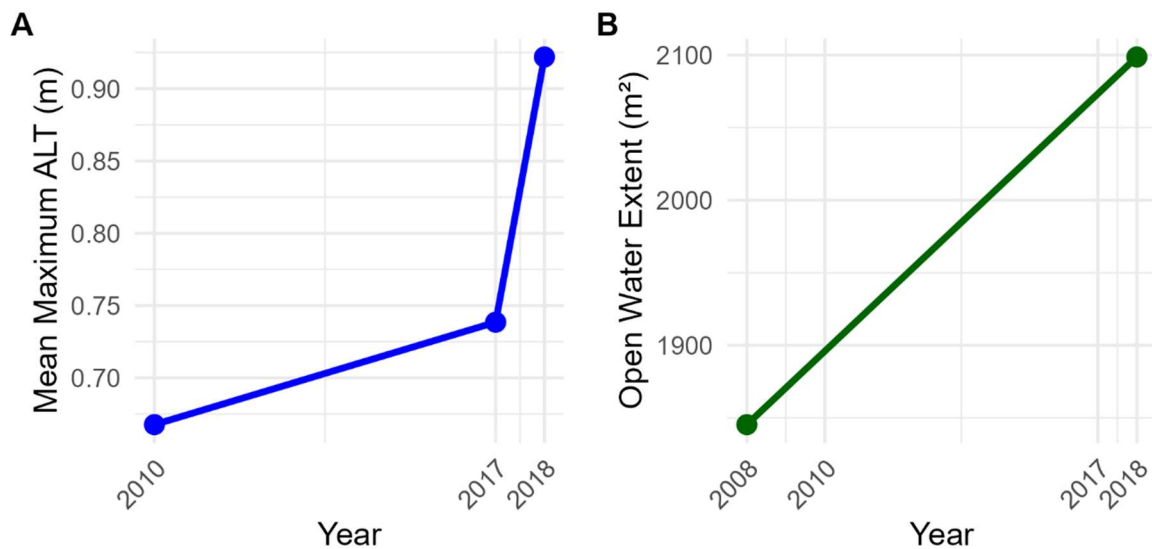


Figure 19. Temporal changes in A) Mean maximum ALT (m, $n = 26$) and B) open water extent (m^2). ALT represents yearly average values for all measurement points (2010–2018), and open water extent is the total mapped open water area for each year (2008–2018).

4.4.3 Regional Active Layer Trends Across Abisko Mire Sites

Mean ALT for all surveyed mires in the Abisko area displayed a strong and significant increase ($R^2 = 0.82$, $p < 0.001$) from 1978 to 2023 (Fig. 20). The lowest mean ALT was 0.48 m in 1978 and the highest 0.98 m in 2021, representing a 104% increase.

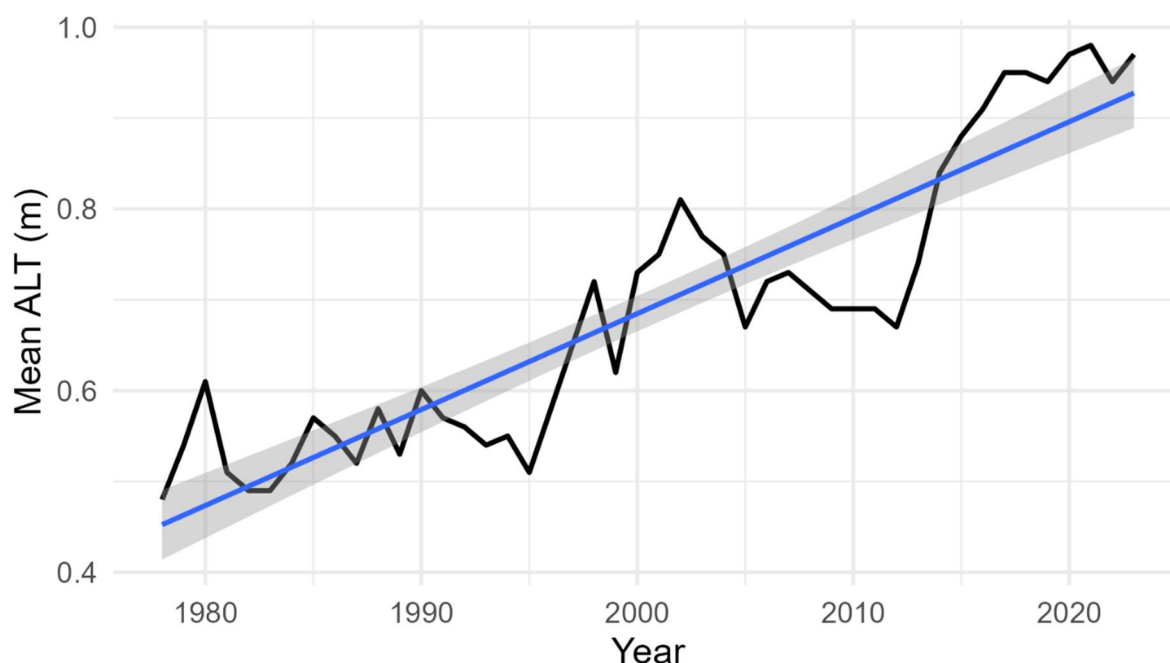


Figure 20. Relationship between mean ALT (m) across nine Abisko valley sites and time (1978–2023). The linear regression line (blue) indicates a significant linear increase ($R^2 = 0.82$, $p < 0.001$), with the confidence interval shown in grey. ALT data are from Åkerman (1998, updated).

4.5 Climate Trends in Abisko

During the full study period (1959–2024), MAT generally exhibited positive trends across most time intervals, except for 2002–2008 (Fig. 21). During this period, a slight decrease was observed. The strongest increase in MAT occurred during the most recent period, 2018–2024.

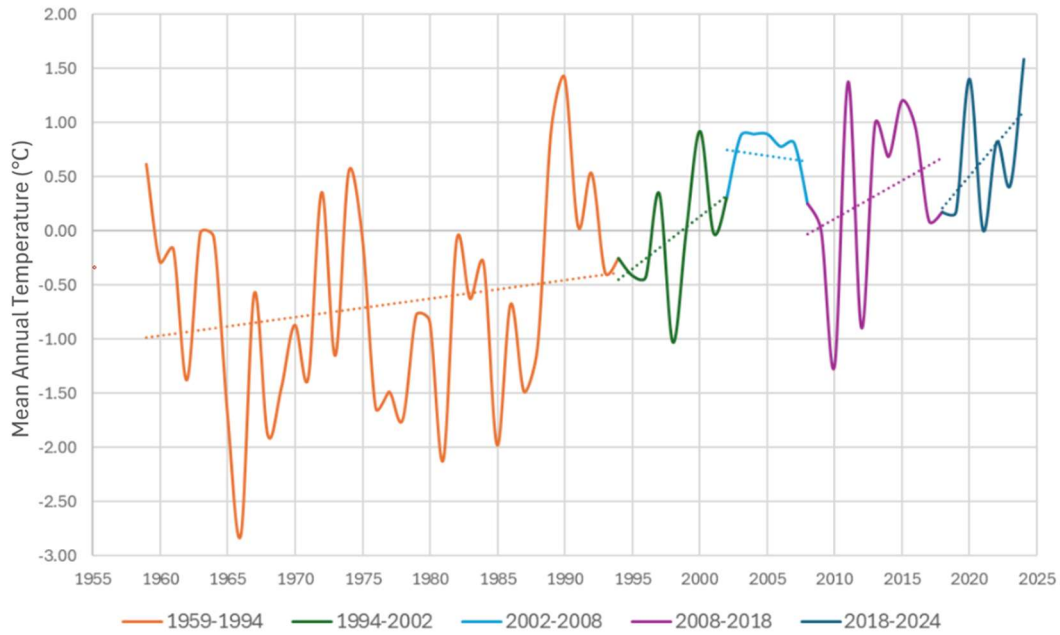


Figure 21. Mean annual temperature (°C) in Abisko for 1959–2024. Trendlines are displayed for the temporal periods 1959–1994, 1994–2002, 2002–2008, 2008–2018 and 2018–2024. Temperature data was obtained from SMHI (n.d.).

Total annual precipitation (TAP) exhibited higher variability between the temporal periods (Fig. 22). Positive precipitation trends were observed for the time intervals 1959–1994, 1994–2002 and 2008–2018, whereas negative trends were seen for 2002–2008 and 2018–2024. Overall, precipitation patterns were less consistent than temperature trends.

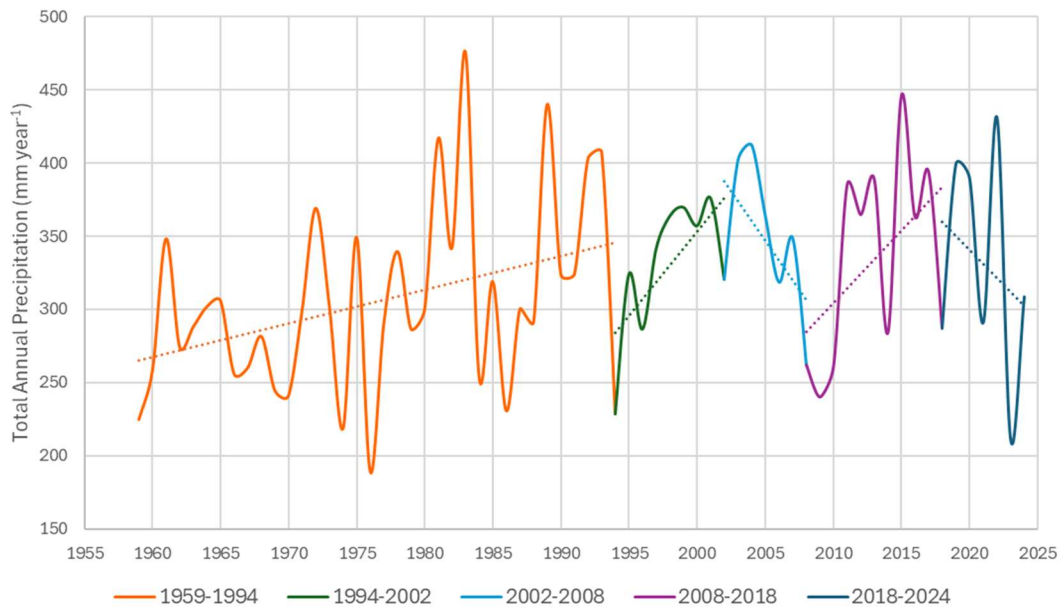


Figure 22. Total annual precipitation (mm yr⁻¹) in Abisko for 1959–2024. Trendlines are displayed for the temporal periods 1959–1994, 1994–2002, 2002–2008, 2008–2018 and 2018–2024. Precipitation data was obtained from SMHI (n.d.).

Temperature and precipitation anomalies for June, July and August (2017–2024) are shown in Figs. 23A and 23B. The greatest positive temperature anomalies occurred in July of 2018 and

in all summer months in 2024. Regarding precipitation, July 2017 exhibited the highest positive anomaly (+60 mm month⁻¹). The most notable negative precipitation anomalies were seen in July 2019 (-42 mm month⁻¹) and July 2023 (-58 mm month⁻¹).

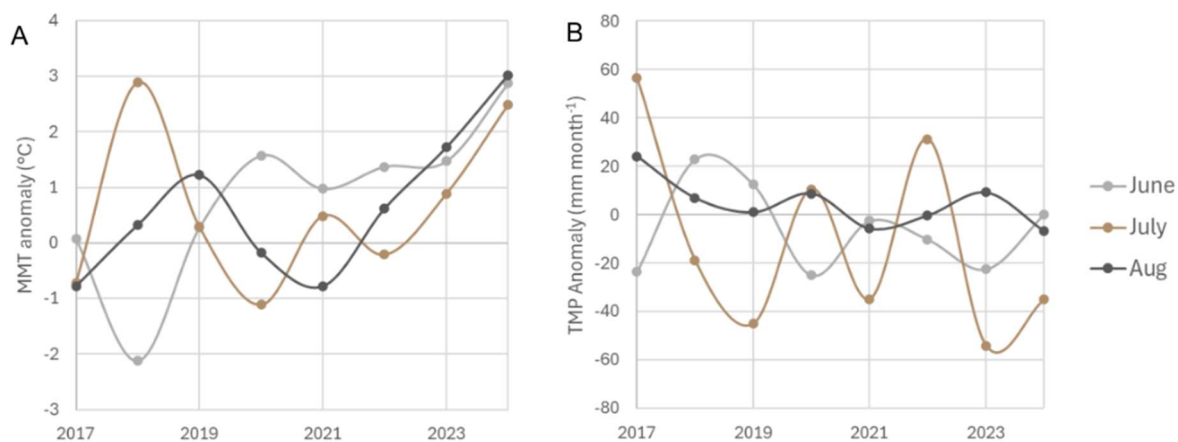


Figure 23. Figures showing monthly anomalies in JJA for the years 2017–2024 for A) mean monthly temperature (MMT, °C) and B) total monthly precipitation (TMP, mm month⁻¹). Anomalies were calculated relative to the long-term mean (1991–2020).

5 Discussion

5.1 Overview of Findings

This study investigated long- and short-term open water dynamics in the Stordalen mire and their relationship to ALT. The results indicate a significant long-term increase in open water extent since 1959, together with an increase in ALT between 2010 and 2018 for all peatland types. Contrastingly, the short-term analysis showed pronounced interannual variability in open water extent and not a consistent increase. Further, no direct relationship between open water change and ALT was found.

5.2 Long-Term Open Water Dynamics (1959-2018)

5.2.1 Consistent Increase in Total Open Water Area

The long-term analysis of open water change revealed a strong increase in total open water extent in the study area, validating part of the first hypothesis (H1). This supports the assumption that there is ongoing thermokarst development in the study area, aligning with previous studies conducted in the mire (Thomas et al., 2025; Varner et al., 2022; Vasile et al., 2026).

The observed increase in open water extent can be linked to reported permafrost and palsa degradation in the mire over the past decades (Johansson et al., 2006; Svensson et al., 1999). De la Barrera Bautista et al. (2022) revealed pronounced subsidence within the palsa mire, where permafrost ice meltwater, precipitation and laterally transported water can accumulate, leading to formation of the observed thermokarst ponds (Seppälä, 2006).

Consistent with these findings, Christensen et al. (2004) reported a total increase of 1200 m² in open water extent between 1970-2000. This is greater than the increase of 660 m² found over a roughly comparable time period (1959–2002) as in the present study, however, their research covered a larger study area. Building on that study, Varner et al. (2022) reported a 35% increase in open water extent from 1970-2014, notably lower than the increase reported in the present study (243–255% depending on MMU). This difference could partly be explained by different study period durations, with the current study spanning 15 years longer than that of Varner et al. (2022). Further, the discrepancies in reported numbers might be attributed to the interchangeability between open water and inundated fen or peatbog wetland (Thomas et al., 2025).

Contrastingly, Wallin (2025) found a decrease in open water extent in the neighbouring palsa mire Storflaket, located across the road from Stordalen, between 1960 and 2018. This may indicate spatial heterogeneity between the two palsa mires. Alternatively, Storflaket could be at a different state of degradation. However, no reasons for this decrease in open water extent were presented by Wallin (2025), as this study mainly focused on palsa degradation and not open water dynamics. Otherwise, the findings of the present study and others conducted in the Stordalen mire align with those of regional studies. Valman et al. (2024) report widespread palsa subsidence and thermokarst formation in 8 Swedish palsa mires. Similarly, in Finland,

marked decreases of -77.3% and -89.7% in palsa extent have been observed in a corresponding study period (1959–2021), with increasing thermokarst as a result (Verdonen et al., 2023). These findings align with patterns of widespread palsa degradation and thermokarst formation reported across the Sub-Arctic.

It is worth noting that the rate of change in open water extent varied between time steps. This suggests that palsa degradation and thermokarst development can be episodic, rather than linear (Jorgenson & Osterkamp, 2005). The most rapid expansion was seen from 2002 to 2008. During this period, precipitation displayed a decreasing trend, but temperatures remained relatively high in comparison to previous years. This indicates that short-term variability in precipitation alone does not explain the observed increase in open water extent. Instead, this pattern may reflect progressive permafrost degradation and hydrological processes, under consistently warm climatic conditions (Johansson et al., 2006; Olefeldt et al., 2021).

It should also be acknowledged that differences in the imagery might have influenced the mapped changes in open water extent. A transition from panchromatic to RGB imagery, as well as increased spatial resolution, occurred between 2002 and 2008. This likely improved the detectability of smaller ponds, thereby potentially contributing to the rapid increase in open water extent between these years. While the total open water extent increased under both tested MMUs, the increase was notably higher under an MMU of 2 m², suggesting that the observed expansion was primarily driven by smaller open water features. Moreover, it highlights that the estimates of open water extent are sensitive to MMU selection.

5.2.2 Temporal Variability in Number of Ponds

During the study period, the total number of ponds increased, however, this increase was not linear. While the number of ponds increased between most time steps, the number of ponds decreased from 1959 to 1994. Despite the overall increase of 90 ponds (MMU = 2 m²) or 40 ponds (MMU = 10 m²), no statistically significant trend in pond number over time was found. Thus, the second half of H1, that the number of ponds would increase over the study period, was not confirmed. As total open water extent increased throughout the whole study period, this may indicate that total open water area is a more stable indicator of thermokarst evolution than pond number. Since thermokarst processes involve both the formation and disappearance of ponds (Seeman & Sannel, 2024), pond abundance alone may not capture the net thermokarst expansion.

The non-significant output of the linear regression analysis could partly be explained by the non-monotonic trend, driven by the decrease in 1994. This could be a result of pond drainage, seasonal drying or ingrowth of vegetation (Jabłońska et al., 2025; Olefeldt et al., 2021). Particularly small ponds can be susceptible to these processes (Seemann & Sannel, 2024), aligning with the notably higher mean and median pond area seen in 1994. These pond dynamics suggest that permafrost thaw does not necessarily result in continuous pond increase.

Thermokarst systems can expand in extent even if the number of ponds decreases, as the ponds can grow, merge and then expand (Seemann & Sannel, 2024). This could explain why in 1994,

the total water extent continued increasing, despite the decreasing number of ponds. Fig. 10 suggests that such expansion and merging can be seen in the southeastern (SE) part of the study area in 1994. Nonetheless, this area is classified as fen (Persson et al., 2012) and does not presently feature any palsa. If this were the case already in 1959–1994, these ponds may not be thermokarst features and are instead influenced by water flows from the nearby lake.

This uncertainty highlights the challenge of distinguishing thermokarst ponds from aerial imagery alone. In 1994, the imagery had lower spatial resolution (1 m) and notably lower contrast than the other years (Fig. 3), thereby complicating the detection of smaller open water features and the differentiation of inundated peat bogs or fens from shallow thermokarst ponds. It is thus a possibility that thermokarst ponds within the palsa and internal fen areas were simply not detectable this year.

After 1994, the number of ponds increased rapidly across the study area. This increase was mainly seen in smaller ponds, as is evident from the much greater increase under an MMU of 2 m² than an MMU of 10 m². This suggests that the open water expansion is primarily driven by small ponds. Small ponds are often the first indicator of local thaw and subsidence (Olefelt et al., 2021), with larger ponds developing later through abovementioned expansion and/or coalescence. This may help explain why pond count can fluctuate while total open water area increases.

Contrasting the findings of this study, Seemann & Sannel (2024) found decreasing trends in the number of thermokarst ponds over the past two decades (2003–2021). Several studies across the Arctic have found similar trends in decreasing thermokarst pond numbers (Bouchard et al., 2014; Necsoiu et al., 2013). Seeman & Sannel (2024) attributed this to drainage, ingrowth of vegetation and shoreline erosion. Simultaneously, they reported increasing mean and median pond size, suggesting drainage of smaller water bodies. Contrastingly, this study found no significant relationship between either mean or median pond size and time. Mean and median pond sizes were instead slightly lower in later years. These differences could be attributed to the studied palsa mires being at different stages of thermokarst. Alternatively, local hydrological and geomorphological variations may cause different drainage patterns.

Despite these differences, both this study and Seeman & Sannel (2024) indicate that thermokarst systems are dynamic. Visual inspection of the mapped ponds in Stordalen indicates rearrangement of thermokarst ponds, with both the disappearance and formation of ponds. This, together with the non-linear pattern, suggests that the study area is characterised by a dynamic pond turnover. Similarly, Seeman & Sannel (2024) found that new ponds formed in their study area, however, not at the same rate as others drained. Together, this highlights how thermokarst landscapes go through cycles of formation, expansion and drainage. Whether Stordalen will transition toward increased pond drainage, as seen in other areas, is unclear, and is subject to further studies.

5.3 Short-Term Open Water Dynamics from UAV Extent (2017-2024)

The short-term analysis of the smaller study area revealed that both pond count and open water area fluctuated strongly from 2017 to 2024. The trends were non-monotonic for both variables, decreasing from 2017 through 2018 and 2019, and then increasing again from 2019 to 2024. Therefore, the second hypothesis (H2), which predicted a continued increase in open water extent and pond count in this period, was not supported. Rather, in this time frame, short-term variability appears stronger than continued open water expansion. Notably, the changes occurred rapidly over a few years, as highlighted by the marked drop in open water area from 1076 m² in 2017 to 96 m² in 2019. This indicates that surface water is highly dynamic in the Stordalen mire.

The interannual fluctuations in open water extent and pond count likely reflect pronounced hydrological variability. This variability may be linked to fluctuations in precipitation, both in terms of snowmelt and rainfall input. Precipitation data shows marked interannual variability in Abisko over the decades. Moreover, summer precipitation anomalies in 2017–2024 might help explain why open water extent dropped so much from 2017 to 2019. 2017 featured anomalously high monthly precipitation in July (60 mm month⁻¹ higher than the 30-year average), whereas 2018 showed an anomaly of -20 mm month⁻¹ and 2019 a notable negative anomaly of more than -42 mm month⁻¹. This suggests that the decrease in open water features in 2019 may partly reflect hydrological conditions and not a sudden disappearance of thermokarst features. The partial recovery seen in 2024 reinforces this idea. Evaporation rates can also vary, partly dependent on air temperatures (Hess, 2014). However, the relationship between air temperatures and open water extent was only visually assessed and no relationship could be revealed.

Seasonal timing likely also affects the amount of detected surface water. Imagery acquisition dates differed between years, with the 2024 imagery captured in early June, the 2019 imagery in mid-August and the other two in July. The water extent in 2024 is thus likely more connected to snow-melt inundation and temporary flooding. The dry year of 2019 was captured at the end of the season and may therefore be affected by seasonal drying. Seasonal thaw depth and water table fluctuations can impact the surface water levels. Persson et al. (2012) show decreasing water table depth, coupled with increasing ALT, in palsa areas in Stordalen over the summer season. For the internal fen area, Persson et al (2012) also found that the water table had lowered slightly by the end of the season. This suggests that the low open water extent in 2019 may be influenced by the late-season timing of the imagery acquisition.

The pronounced interannual variability observed in this study also highlights the sensitivity of very high-resolution UAV imagery to hydrological changes within the mire. Comparing the mean pond area derived from the RF classified UAV imagery to that of the manually interpreted orthophotos, it is evident that the first methodology better captures small open water features. Nevertheless, the RF classification achieved slightly lower accuracy assessment scores, which indicated overclassification of open water. Despite this, the methodology aided the detection of rapid hydrological fluctuations that might only be detectable at such high resolutions.

Aligning with the findings of this study, Thomas et al. (2025) also show variability in open water in the Stordalen mire between years (2014–2022). However, the interannual pattern reported in their study differed slightly from the trends identified in the present study. While in Thomas et al. (2025), open water area was high in 2017 and slightly lower in 2018, it appeared to be high again in 2019, contrasting the findings of this study. This difference may partly be attributed to their imagery being captured at other times in the season (late August and early September). Further, the difference in the classification methods used may contribute to the discrepancies. Finally, slightly disparate definitions of open water applied in the studies could lead to different results.

5.4 Active Layer Thickness Dynamics

ALT increased significantly in the study area from 2010 to 2018, for all peatland types. This further supports the assumption that there is ongoing permafrost thaw in the Stordalen mire. The deepening of the AL is consistent with previous studies conducted in Stordalen (Christensen et al., 2004; Johansson et al., 2006) and regional trends in the Abisko area (Åkerman & Johansson, 2008), as well as reported widespread increases in ALT across the NH (Li et al., 2022). The ALT increase was, however, not linear, with no significant difference between 2010 and 2017, but a strong increase in 2018. This suggests enhanced thaw in 2018. In turn, this could be a result of climatic control on ALT, as 2018 featured anomalously high July temperatures and ALT is partly influenced by increased air temperatures (Liu, 2023). It is worth noting, however, that several other parameters, such as snow cover thickness and soil moisture content, exert control on ALT (Peng et al., 2023).

Alternatively, the rapid increase in ALT might also be thermokarst-related abrupt thaw, which has been observed in permafrost landscapes (Webb et al., 2025).

All peatland types exhibited similar positive thaw trends, as indicated by the non-significant interaction effect. This suggests that climate warming effects are widespread across the mire and that all peatland types are affected. However, the absolute ALT values differ between palsa bog and fen. Similarly, Muir et al. (2025) found variations in thermal regime between fen and palsa in a Canadian palsa mire. This can partly be attributed to differences in moisture and vegetation cover. While the dry peat in palsa can insulate the underlying permafrost, the moisture in the wet fen may showcase deeper thaw due to the higher thermal conductivity of wet peat (Seppälä, 2010). Interestingly, there was no statistically significant difference between internal fen and the other two peatland classes. This might be because internal fen is a transitional stage between elevated palsa bogs and fully thawed fens (Persson et al., 2012). Despite these clear differences in ALT between peatland types, directly linking thaw to open water dynamics is complex, due to the influence of local hydrology and geomorphology.

5.5 Relationship Between Open Water Dynamics and Active Layer Thickness

While both open water extent and ALT increased in corresponding temporal periods, no significant local relationship between them was found in this study. Therefore, the third hypothesis (H3) was not supported. This suggests that thermokarst and open water development are not controlled by ALT alone, but by multiple interacting factors (Olefelt et al., 2016). The

increasing ALT, as outlined in the previous section, indicates widespread permafrost thaw in the mire. This thaw creates conditions favourable for open water formation, although where the ponds form might further depend on hydrological and geomorphological conditions (Olefelt et al., 2016; Olefeldt et al., 2021).

One explanation for the weak local relationship between ALT and open water could be that the two variables have different physical meanings and represent different aspects of thermokarst dynamics. While ALT represents vertical thaw at specific locations (Åkerman, 1998; Persson et al., 2012), open water extent is the horizontal surface response to subsidence and water accumulation (Seppälä, 2006). Therefore, pond formation and water expansion are likely not only controlled by thaw depth, but also by drainage pathways and the properties of peat (Fewster et al., 2023; Somera et al., 2025).

Additionally, hydrological processes likely weakened the local relationship between ALT and open water extent. In Stordalen, Persson et al. (2012) found that ALT and water table depth covaried seasonally in the palsa areas. However, water redistribution likely makes this relationship more complex. The water contributing to thermokarst ponds does not only originate from thawed permafrost ice and suprapermafrost water, but from precipitation and snowmelt inputs, as well as laterally flowing water in the mire system (Fewster et al., 2023; Somera et al., 2025). The water source areas may thus differ from the pond locations.

Furthermore, water accumulation is influenced by drainage (Olefelt et al., 2021; Seeman & Sannel, 2024). These processes likely extend beyond the 10-metre buffer zone applied to the ALT measurement points in this study. Interestingly, a majority of the palsa ALT points exhibited no change in open water extent within their buffer zones, which further indicates a weak coupling at the local scale between increases in ALT and open water change. This is also supported by Verdonen et al. (2023), who found that point-based ALT measurements do not always reflect local permafrost degradation in palsas. Moreover, water accumulates in depressions, which may be located more than 10 metres from the measurement points. Together, this might help explain why ALT measurements may not directly correspond to nearby open water expansion.

Additionally, AL deepening and thermokarst pond formation may not occur synchronously. Permafrost thaw can occur both gradually and abruptly, with thermokarst formation exhibiting a delayed response (Webb et al., 2025). Such threshold behaviour in thermokarst could explain this unmatched relationship. Therefore, increases in ALT from 2010 to 2018 may not yet have resulted in thermokarst formation within the analysed buffer zones. Conversely, the ponds delineated in this period may be a result of earlier thaw processes. As highlighted by Johansson et al. (2006), there has been ongoing thaw in the Stordalen mire in the past decades. AL deepening initiating pond formation may have occurred at any time in this period and detected changes in open water extent from 2008 to 2018 may instead be attributed to the previously outlined hydrological processes. In conclusion, temporal disconnect could partly explain why no statistically significant relationship between ALT and nearby open water change was found in this study.

5.6 Methodological Considerations and Limitations

While the results provide insights into both long- and short-term dynamics of open water and AL change, there are several methodological considerations that should be taken into account when interpreting these findings. A key limitation relates to differences in spatial resolution across the multi-decadal dataset. This study combined historical aerial photography with recent UAV-derived imagery. A similar approach was used by Verdonen et al. (2023). However, the varying spatial resolutions in the imagery can lead to inconsistent detection of open water features across the years. This can, for instance, be seen in the lack of smaller features detected in 1994, which may be attributed to the lower spatial resolution and contrast in the 1994 imagery, compared to other years. Further, using different MMUs yielded different results in both open water extent and number of ponds. A lower MMU of 2 m² resulted in markedly higher values of pond numbers, indicating the important contribution of smaller thermokarst features. With varying spatial resolutions, these smaller features may be inconsistently included across the years.

Another important source of uncertainty stems from the classification of open water features, across both datasets and methods. In the aerial photographs, particularly in the panchromatic imagery, it was noted during the digitisation that differentiating between vegetated wetlands and open water was at times difficult. Although higher spatial resolution facilitated this distinction, the RF classified UAV imagery still achieved lower accuracy scores than the manual digitisation. The accuracy assessment of the RF classification indicated an overclassification of open water. This was likely due to inundated *Sphagnum* bogs or sedge fens being classified as open water. Similar classification challenges have been highlighted in earlier studies. Thomas et al. (2025) handled this limitation by grouping open water areas and degraded permafrost areas together. As specifically open water was of interest in this study, such an approach would have been unsuitable. However, using open water as a proxy for thermokarst may have resulted in missed thermokarst features, as vegetated thermokarst ponds are known to be present in the Stordalen mire and other palsa systems (Jabłońska et al., 2025; Vasile et al., 2026).

Additionally, manual digitisation introduces subjectivity, and the use of self-assessment of accuracy further contributes to this limitation. Ideally, field validation of the classifications would have been conducted. Given more time to conduct the study, this might have been feasible for the recent UAV imagery, but it would not have been possible for the historical datasets.

Temporal inconsistencies between datasets constitute another limitation. Firstly, the different acquisition dates of the UAV imagery likely impacted the amount of open water detected across the years, as described in section 5.3, potentially contributing to the detected pattern of interannual variability in open water extent in recent years. Furthermore, this study combined a long-term (1959–2024) time series of open water extent with a markedly shorter ALT record. This mismatch may have limited causal interpretation of the relationship between open water change and ALT dynamics. Despite this, the results provided some valuable insights.

A further limitation concerns the spatial representativeness of the study area. The southeastern (SE) part of the study area was classified as fen by Persson et al. (2012) and is thus not a palsa. It is not established whether this area was a palsa at the beginning of the study period (1959). The open water features in this area may be hydrologically connected to the nearby lake, rather than the thermokarst system in the mire. Olefeldt et al. (2021) suggest that hydrological influence of other water bodies can inhibit palsa formation due to heat transfer. This supports the idea that the mapped ponds in the SE area may not be of thermokarst origin. However, this is not established but rather highlights a potential limitation. Further, the water extent in this part of the study area is relatively stable in comparison to the open water extent in the other areas. This indicates that the trends in open water extent found in this study still show thermokarst development.

While these limitations should be considered when interpreting the results, the findings still provide meaningful insights to long- and short-term open water and ALT dynamics in the Stordalen mire.

5.7 Recommendations for Future Studies

To improve and build on this research, future studies could combine remote sensing analyses with field measurements to better distinguish open water and vegetated thermokarst features from inundated wetland, as well as to improve classification validation. Together with continued ALT monitoring, this could help clarify whether delayed responses exist between active layer deepening and local pond development.

Further, future studies should aim to apply consistent dates for data acquisition to reduce the influence of seasonal hydrological variability on mapped open water extent. Alternatively, using temporally denser datasets could capture short-term and seasonal fluctuations in pond dynamics. The hydrological controls on thermokarst pond formation could also be investigated by including water table measurements and identifying drainage pathways. This might help understand why the local relationship between ALT and open water change was weak in this study.

In terms of methodology, an expanded assessment on how MMU selection influences open water dynamics would be valuable. Thus, the contribution of small ponds to thermokarst development could be further understood. Finally, future studies could combine gas flux measurements with remotely sensed pond dynamics to assess the effect of thermokarst development on carbon cycling and CH₄ emissions. While C fluxes have previously been studied for different land cover classes in Stordalen, the relationship between thermokarst pond dynamics and variability in greenhouse gas emissions could be further investigated.

6 Conclusion

This thesis aimed to assess how thermokarst-related open water dynamics have developed over time in the Stordalen mire and how these changes relate to active layer thickness. Open water extent increased markedly from 1959 to 2018, which indicates ongoing thermokarst development. While the total number of ponds increased between 1959 and 2018, the number of ponds showed a non-monotonic trend and not a statistically significant linear increase. This suggests that thermokarst expansion does not always entail a continuous increase in the number of ponds. Moreover, the short-term UAV analysis (2017–2024) revealed high interannual variability in both pond extent and abundance. Active layer thickness increased significantly from 2010 to 2018, signalling active permafrost thaw in the mire. Despite this, no significant local relationship between active layer thickness and open water change was established.

These findings highlight that thermokarst systems in palsa mires are dynamic, with pond formation, drainage and expansion occurring within rather short time frames. Small ponds appear to be of particular importance in these processes. Further, the results suggest that thermokarst development is not controlled solely by active layer deepening, but also by hydrological and geomorphological processes.

Together, the findings of this study contribute to the understanding of landscape change in thawing permafrost peatlands under the influence of climate change. The study also shows that combining historical aerial imagery with contemporary high-resolution UAV data is valuable for understanding long-term thermokarst-related open water dynamics. To understand future hydrological and carbon-related changes in permafrost peatlands and palsa mires, continued monitoring of these changes is crucial.

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