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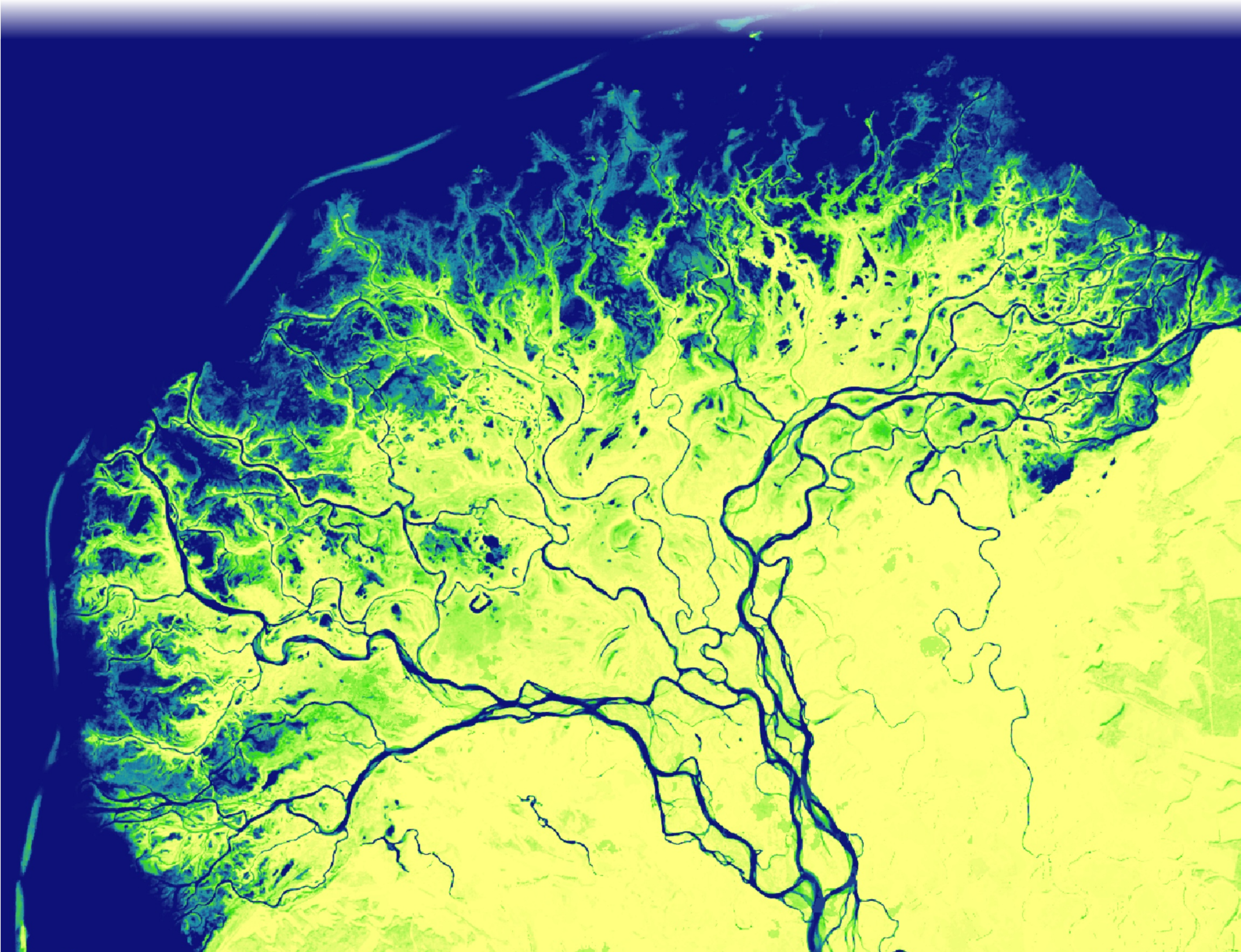
# Monitoring Water Availability in Northern Inland Waters from Space

Saeid Aminjafari



Doctoral Thesis in Physical Geography at Stockholm University, Sweden 2023

# Monitoring Water Availability in Northern Inland Waters from Space

**Saeid Aminjafari**

Academic dissertation for the Degree of Doctor of Philosophy in Physical Geography at Stockholm University to be publicly defended on Thursday 12 October 2023 at 13.00 in Högbomsalen, Geovetenskapens, 3rd floor, Svante Arrhenius väg 12 and online via Zoom: https://stockholmuniversity.zoom.us/j/65376314946.

**Abstract**

River deltas and lakes support biodiversity and offer crucial ecosystem services such as freshwater provision, flood control, and fishing. However, climate change and human activities have affected deltas and lakes globally, altering the services they provide. Since delta and lake surface water occurrence and water levels respond to climate change and anthropogenic activities, we need to monitor their variations to understand the potential drivers for effective water management strategies. However, important deltas like the Selenga River Delta (SRD) in Russia lack a detailed analysis of water occurrence. Regarding lake water level, there has been a decline in the number of gauging stations globally, due to installation and maintenance costs. For example, Sweden has ~100,000 lakes which are sources of freshwater and hydro-power, but only 38 lakes have long and continuous in-situ records of water level.

As satellite data are reliable alternatives for conventional methods to monitor deltas and lakes, I employed Earth Observations (EO) to quantify changes in surface water occurrence in the SRD and water levels in Swedish lakes and identify their main drivers. I also developed and explored a novel methodology for lake water level estimation based on Differential Interferometric Synthetic Aperture Radar (D-InSAR) by calculating the six-day phase differences in 30 Swedish lakes.

To achieve these objectives, I trained and applied a Maximum Likelihood classification to Landsat images from 1987 to 2020 and quantified surface water occurrence and its changes in the SRD. I found that surface water occurrence in 51% of the delta experienced a decrease. As the Selenga River is the only river flowing into the SRD, the change in surface water occurrence in the SRD correlated with river discharge, but not with the river suspended sediment concentration, the lake water level in the outlet of the SRD, or evapotranspiration over the delta.

In Sweden, I used satellite altimetry data from ERS-2, ENVISAT, JASON-1,2,3, SARAL, and Sentinel-3A/B to quantify water levels in 144 lakes from 1995-2022. I found that 52% of the lakes showed increasing trends (mostly in the north) and 43% decreasing trends (mostly in the south). Water level trends and variabilities did not correlate strongly with hydroclimatic changes (precipitation and temperature) but differed in regulated lakes compared to unregulated ones, both in the north and in the south of Sweden.

The results of the D-InSAR method for water level estimation in two Swedish lakes (Hjälmaren and Solnen) showed that with water level changes smaller than a complete SAR phase, the phase changes correlate with in-situ water level changes with a minimum Root Mean Square Error of 0.43 cm in some pixels. In all 30 lakes, I accumulated the phase changes of each pixel throughout the whole number of interferograms to construct water levels. This method replicated the direction of water level changes shown by high Pearson's correlations in at least one pixel in each lake.

This thesis highlights the importance of EO for estimating surface water occurrence and lake water levels and brings focus to the future of EO through advanced space missions such as Surface Water and Ocean Topography (SWOT) and NASA-ISRO Synthetic Aperture Radar (NISAR). The findings underscore the need to continuously monitor lake water level and occurrence to adapt to climate change and understand the effects of water-regulatory schemes.

**Keywords:** *Water occurrence, Lake water level, Remote sensing, Altimetry, D-InSAR.*

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**Department of Physical Geography**

Stockholm University, 106 91 Stockholm

MONITORING WATER AVAILABILITY IN NORTHERN INLAND WATERS FROM SPACE

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# Abstract

River deltas and lakes support biodiversity and offer crucial ecosystem services such as freshwater provision, flood control, and fishing. However, climate change and human activities have affected deltas and lakes globally, altering the services they provide. Since delta and lake surface water occurrence and water levels respond to climate change and anthropogenic activities, we need to monitor their variations to understand the potential drivers for effective water management strategies. However, important deltas like the Selenga River Delta (SRD) in Russia lack a detailed analysis of water occurrence. Regarding lake water level, there has been a decline in the number of gauging stations globally, due to installation and maintenance costs. For example, Sweden has $\approx$100,000 lakes which are sources of freshwater and hydro-power, but only 38 lakes have long and continuous in-situ records of water level.

As satellite data are reliable alternatives for conventional methods to monitor deltas and lakes, I employed Earth Observations (EO) to quantify changes in surface water occurrence in the SRD and water levels in Swedish lakes and identify their main drivers. I also developed and explored a novel methodology for lake water level estimation based on Differential Interferometric Synthetic Aperture Radar (D-InSAR) by calculating the six-day phase differences in 30 Swedish lakes.

To achieve these objectives, I trained and applied a Maximum Likelihood classification to Landsat images from 1987 to 2020 and quantified surface water occurrence and its changes in the SRD. I found that surface water occurrence in 51% of the delta experienced a decrease. As the Selenga River is the only river flowing into the SRD, the change in surface water occurrence in the SRD correlated with river discharge, but not with the river suspended sediment concentration, the lake water level in the outlet of the SRD, or evapotranspiration over the delta.

In Sweden, I used satellite altimetry data from ERS-2, ENVISAT, JASON-1,2,3, SARAL, and Sentinel-3A/B to quantify water levels in 144 lakes from 1995-2022. I found that 52% of the lakes showed increasing trends (mostly in the north) and 43% decreasing trends (mostly in the south). Water level trends and variabilities did not correlate strongly with hydroclimatic changes (precipitation and temperature) but differed in regulated lakes compared to unregulated ones, both in the north and in the south of Sweden.

The results of the D-InSAR method for water level estimation in two Swedish lakes (Hjälmaren and Solnen) showed that with water level changes smaller than a complete SAR phase, the phase changes correlate with in-situ water level changes with a minimum Root Mean Square Error of 0.43 cm in some pixels. In all 30 lakes, I accumulated the phase changes of each pixel throughout the whole number of interferograms to construct water levels. This method replicated the direction of water level changes shown by high Pearson's correlations in at least one pixel in each lake.

This thesis highlights the importance of EO for estimating surface water occurrence and lake water levels and brings focus to the future of EO through advanced space missions such as Surface Water and Ocean Topography (SWOT) and NASA-ISRO Synthetic Aperture Radar (NISAR). The findings underscore the need to continuously monitor lake water level and occurrence to adapt to climate change and understand the effects of water-regulatory schemes.

## Sammanfattning

Floddeltan och sjöar stöder den biologiska mångfalden och erbjuder viktiga ekosystemtjänster som färskvattenförsörjning, översvämningsbekämpning och fiske. Klimatförändringar och mänskliga aktiviteter har dock påverkat deltan och sjöar globalt och förändrat de tjänster de tillhandahåller. Eftersom förekomsten av ytvatten i delta och sjöar och vattennivåerna svarar på klimatförändringar och antropogena aktiviteter måste vi övervaka deras variationer för att förstå de potentiella drivkrafterna för effektiva vattenförvaltningsstrategier. Viktiga deltan som Selenga River Delta (SRD) i Ryssland saknar dock en detaljerad analys av vattenförekomsten. När det gäller sjöarnas vattennivå har antalet mätstationer minskat på grund av installations- och underhållskostnader. Till exempel har Sverige 100 000 sjöar som är källor till sötvatten och vattenkraft, men endast 38 sjöar har långa och kontinuerliga in situ-register över vattennivån.

Eftersom satellitdata är tillförlitliga alternativ till konventionella metoder för att övervaka deltan och sjöar, har jag använt satellitobservationer för att kvantifiera förändringar i ytvattenförekomst i SRD och vattennivåer i svenska sjöar och identifiera deras huvudsakliga drivkrafter. Jag har vidare utvecklat och utforskat en ny metod för uppskattning av sjövattennivån baserad på Differential Interferometric Synthetic Aperture Radar (D-InSAR) genom att beräkna sexdagars fasskillnader i 30 svenska sjöar.

För att uppnå dessa mål har jag övat på, samt tillämpat en Maximum Likelihood-klassificering på Landsat-bilder från 1987 till 2020 och kvantifierade ytvattenförekomst och dess förändringar i SRD. Jag har nått slutsatsen att ytvattenförekomsten i 51 % av deltat upplevt en minskning. Eftersom Selengafloden är den enda flod som rinner ut i SRD, korrelerade förändringen i ytvattenförekomsten i SRD med flodutsläpp, men inte med flodens suspenderade sedimentkoncentration, sjövattennivån i SRD:s utlopp eller evapotranspiration över deltat.

I Sverige använde jag satellithöjdmätningsdata från ERS-2, ENVISAT, JASON-1,2,3, SARAL och Sentinel-3A/B för att kvantifiera vattennivån i 144 sjöar från 1995-2022. Jag fann att 52 % av sjöarna visade ökande trender (mestadels i norr) och 43 % minskande trender (mestadels i söder). Vattenståndstrender och variationer korrelerade inte starkt med hydroklimatiska förändringar (nederbörd och temperatur) men skilde sig åt i reglerade sjöar jämfört med oreglerade sjöar både i norra och södra Sverige.

Resultaten av D-InSAR-metoden för uppskattning av sjövattennivån visade att i två svenska sjöar (Hjälmaren och Solnen) med vattennivåförändringar mindre än en fullständig SAR-fas, korrelerar fasförändringarna med in situ-vattennivåförändringar med ett minsta rotmedelkvadratfel på 0,43 cm i vissa pixlar. I 30 andra sjöar ackumulerade jag fasförändringarna för varje pixel genom hela antalet interferogram för att konstruera vattennivåer. Denna metod replikerade riktningen för vattennivåförändringar som visas av höga Pearsons korrelationer i minst en pixel i varje sjö.

Denna avhandling belyser vikten av satellitdata för att uppskatta ytvattenförekomst och sjövattennivå och sätter fokus på framtiden för jordobservationer genom avancerade rymduppdrag som ytvatten och havstopografi (SWOT) och NASA-ISRO Synthetic Aperture Radar (NISAR). Resultaten understryker behovet av att kontinuerligt övervaka sjövattennivåer och förekomst för att anpassa sig till klimatförändringar och förstå effekterna av vattenreglerande system.

## Dissertation content

This doctoral compilation dissertation consists of a summarising text and the 4 articles listed below.

**I** **Aminjafari S**, Brown I.A, Chalov S, Simard M, Lane C.R, Jarsjö J, Darvishi M, and Jaramillo F. 2021. Drivers and extent of surface water occurrence in the Selenga River Delta, Russia. Journal of Hydrology: Regional Studies 38:100945. https://doi.org/10.1016/j.ejrh.2021.100945.

**II** **Aminjafari S**, Brown I.A, Frappart F, Papa F, Blarel F, Vahidi Mayamey F, and Jaramillo F. (under review). Assessing the effects of regulation on Swedish lake water levels with satellite altimetry.

**III** **Aminjafari S**, Brown I.A, and Jaramillo F. (under review). Evaluating D-InSAR performance to detect small water level fluctuations in lakes.

**IV** **Aminjafari S**, Brown I.A, Vahidi Mayamey F, and Jaramillo F. (under review). The potential of D-InSAR for water level estimation in Swedish lakes.

## Author contributions

The contributions from listed authors are divided as follows for each article.

**I** **SA**: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Writing – original draft, Visualization. **IB**: Conceptualization, Methodology, Formal analysis, Data curation, Writing – review, editing, Supervision, Funding acquisition. **SC**: Conceptualization, Methodology, Formal analysis, Resources, Data curation, Writing – review, editing. **MS**: Methodology, Formal analysis, Writing – review, editing. **CL**: Methodology, Formal analysis, Resources, Writing – review, editing. **JJ**: Conceptualization, Methodology, Formal analysis, Writing – review, editing, Funding acquisition. **MD**: Methodology, Formal analysis, Writing – review, editing. **FJ**: Conceptualization, Methodology, Formal analysis, Investigation, Resources, Data curation, Writing – review, editing, Supervision, Project administration, Funding acquisition.

**II** **SA**: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Writing original draft, Visualization, Data Curation, Writing, review, editing. **IB**: Conceptualization, Methodology, Software, Formal analysis, Writing, review, editing, Supervision. **FF**: Methodology, Software, Validation, Formal analysis, Data Curation, Writing, review, editing. **FP**: Methodology, Software, Validation, Formal analysis, Data Curation, Writing, review, editing. **FB**: Methodology, Software, Formal analysis, Writing, review, editing. **FM**: Methodology, Software, Formal analysis, Writing, review, editing. **FJ**: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Writing original draft, Data Curation, Writing, review, editing, Supervision, Funding acquisition, Project administration.

**III** **SA**: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Writing - Original Draft, Visualization. **IB**: Conceptualization, Methodology, Formal analysis, Data Curation, Writing - Review, Editing, Supervision, Funding acquisition. **FJ**: Conceptualization, Methodology, Formal analysis, Investigation, Resources, Data Curation, Writing - Review, Editing, Supervision, Project administration, Funding acquisition

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# Contents

# 1 Introduction

Surface freshwater is the lifeblood of Earth and a crucial component of human existence (Papa et al., 2023). Surface water bodies are the primary source of freshwater for urban and agricultural use and ensure food production. They also serve as habitats for aquatic and terrestrial species and provide numerous ecosystem services to humans, such as fishing and recreational opportunities (Palmer et al., 2015).

Despite significant advancements in hydrologic sciences regarding surface water bodies (e.g., the development of new hydrologic models, remote sensing applications, and implementation of machine learning and cloud computation in hydrology), our understanding of their past, current, and future changes and their dynamic behavior remains limited globally (Alsdorf et al., 2007; Cooley et al., 2021). We still have substantial challenges regarding the accuracy and the limited spatiotemporal resolutions associated with estimating surface water bodies' extent and water levels and their changes and variability (Alsdorf et al., 2007; Calmant et al., 2008; VanDeWeghe et al., 2022). If accurately estimated, these variables and their changes deliver vital information on the current and future state of the freshwater system and, ultimately, facilitate effective water management strategies (Lee et al., 2022; Palmer et al., 2015; Xiang et al., 2021). Moreover, they signal the impacts of climate change (e.g., drought and floods) and the responses and resilience of these water resources and ecosystems (Schwatke et al., 2020).

However, in-situ freshwater measurements have a low spatial resolution hindering our understanding of changes in water bodies (Xiang et al., 2021). Additionally, the number of existing stations used for measurement is declining due to the challenges of installing and maintaining measuring equipment, particularly in remote and mountainous regions (Alsdorf et al., 2007; Cooley et al., 2021; Xiang et al., 2021). Therefore, to understand freshwater systems and their spatial and temporal changes, it is necessary to obtain high-resolution observations at a low cost and with rapid and accurate processing techniques. Satellite sensors can provide high-density observations over water bodies (Zhang et al., 2020).

The aim of this thesis is to use Earth Observations (EO) to understand changes in water availability in northern inland waters. To achieve this aim, I defined three objectives. The primary and secondary objectives are to quantitatively assess surface water extent and lake water levels, and their spatiotemporal variations at northern latitudes with remotely sensed observations, and perform a detailed analysis of the potential underlying factors influencing these changes, respectively. The third objective is to develop and explore the potential of new methodologies for measuring lake water levels. The thesis specifically focuses on the SRD and Swedish lakes located at high northern latitudes ($> 50°$) with important and diverse ecosystem services (Figure 1).

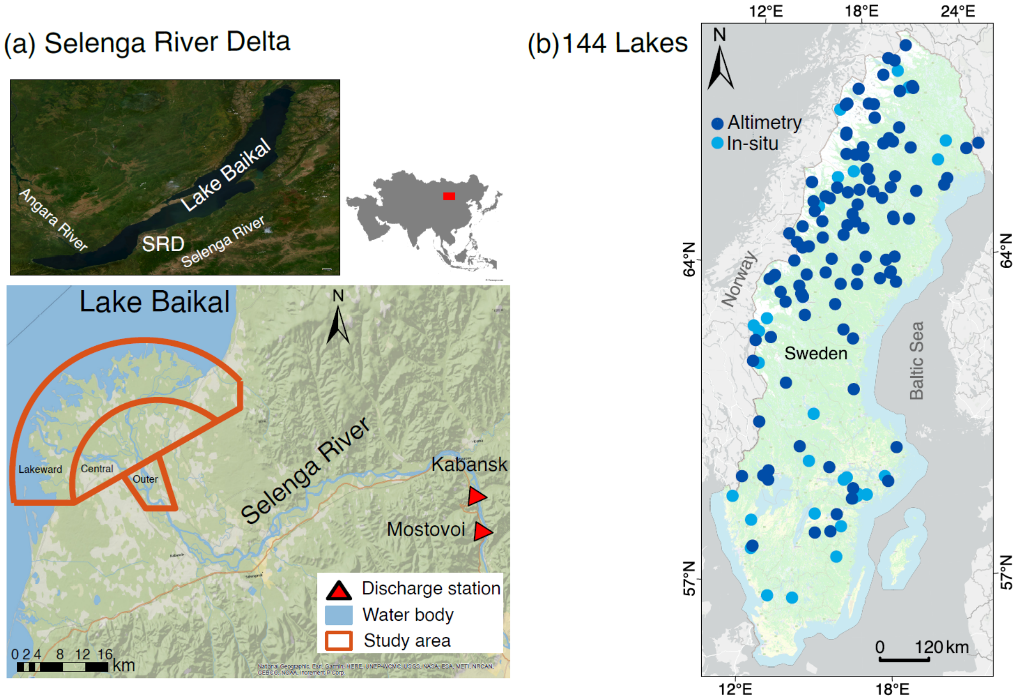


Figure 1. The location map of the two study areas covered in this thesis, **(a)** the Selenga River Delta (SRD), in Paper I, I studied the water occurrence and its change and the possible drivers of the change in the SRD **(b)** 144 Swedish lakes, in Paper II, I studied the changes in the water level of these lakes, and in Paper III and IV, I developed D-InSAR methodology to estimate the water level. Panel a is modified from Paper I (Aminjafari et al., 2021) with a satellite image from Earthstar Geographics, and panel b is from Paper II.

## 1.1 A review of remote sensing for measuring inland surface water extent and water levels

### 1.1.1 Remote sensing of surface water extent

Utilizing satellite optical imagery to track surface water extent is a viable approach due to its low cost and rapid implementation, which has its roots in the CORONA mission employed in the 1960s. First used for military purposes, then mission data became publicly available in 1995 (Altmaier and Kany, 2002; Gardelle et al., 2010). Since then, the technique has undergone continuous development through the launch of more advanced satellites such as Landsat missions and Sentinel-2 (Chen and Zhao, 2022; Yao et al., 2019). Due to the limitations of optical imagery in detecting surface water below vegetation and clouds, and during nighttime, Synthetic Aperture Radar (SAR) has emerged as an additional source of data for monitoring surface water extent since 1992. The first SAR sensor was the Japanese Earth Resources Satellite-1 (JERS-1), and the SAR technology has improved with the advent of newer SAR satellite sensors, such as Sentinel-1 since 2014 (Chen and Zhao, 2022; Papa et al., 2023), and the NASA-ISRO Synthetic Aperture Radar (NISAR) mission in near future, a joint project between the American National Aeronautics and Space Administration (NASA) and the Indian Space Research Organisation (ISRO; Rosen and Kumar, 2021).

The new processing and classification methods such as machine learning have led to more accurate, rapid, and spatially comprehensive extraction of water extent (e.g., An and Rui, 2022; Isikdogan et al., 2017; Lu et al., 2021), and cloud computation platforms such as Google Earth Engine allow fast and automatic processing of large EO data over large areas without the need for high-performance local computers (Aziz et al., 2020; Markos et al., 2023; Yue et al., 2023).

The studies using EO for water extent mapping are divided into a combination of two main categories; 1) global or local studies and 2) long-term time series or short-term/single-time analysis.

Global-scale datasets of water extent derived from satellite images such as Landsat and Sentinel-2 quantify the changes in surface water extent (Allen and Pavelsky, 2018; Donchyts et al., 2016; Pekel et al., 2016). Nevertheless, due to the global-scale coverage and the computational complexity associated with large data, these studies used simple techniques such as unsupervised classifications without training data, which may result in reduced accuracy at a local scale (Foroughnia et al., 2022). Therefore, there is a need for accurate surface water mapping based on supervised classification for deltas lacking these datasets such as the SRD.

Short-term or single-time analysis of surface water extents has been done on local scales (e.g., Chini et al., 2017; Lane et al., 2015; Li et al., 2022a). The aims of these studies are to evaluate and improve classification methods (Li et al., 2023; Li et al., 2022b; Zhao et al., 2023) or construct a high-resolution inventory of wetlands and deltas (Mullen et al., 2023; Wieland et al., 2023). For example, Lane et al. (2015) used high-resolution Worldview-2 satellite images to map the SRD. However, the single-time studies have generally provided a single snapshot of surface water extent taken on a specific day and do not present the evolution over time. Moreover, the main focus of these studies are remote sensing method development and not hydrologic analysis. Therefore, current studies have not fully addressed important hydrologic questions regarding surface water extent and its changes and drivers, limiting our understanding of hydrologic processes. This is due to their processing methods and simplified global-scale analysis or ignoring the long-term changes.

Regarding surface water extent and variations, the Selenga River Delta (SRD) is selected as a case study due to its crucial function in the hydrology of Lake Baikal and its importance within the hydrologic context of Russia. For instance, the SRD reduces 77-99% of various metals' concentration (mining pollutants) in the Selenga River before flowing into Lake Baikal (Chalov et al., 2017). The hydrological connectivity between channels and water bodies or inundated islands in a delta system plays an important role in the water- and sediment transport in that delta (Hiatt et al., 2018). The nutrient transport and sediment deposition, as a result of the stream network and the connection between floodplains in a delta, is a key factor in deltaic landscape evolution, and its biodiversity of flora and fauna (Hiatt and Passalacqua, 2015). There are many factors influencing the connectivity and the formation of delta systems such as the river discharge into the delta, tides (in the case of coastal deltas), wind, delta size, and plant patchiness (Hiatt and Passalacqua, 2015; Piliouras and Kim, 2019). For example, the seasonally inundated islands in the SRD influence the metal flow into Lake Baikal (Shinkareva et al., 2019). Therefore, studying hydrologic connectivity in a delta is important for understanding the processes that control the functions of the delta, for example in reducing pollutants and conserving biodiversity. Studying water occurrence with EO is a fast and efficient way to understand the channel streams, inundated islands, and hydrologic connectivity in a delta system. The occurrence of severe droughts and a reduction in river discharge in the Selenga River basin during the past two decades (Shinkareva et al., 2019) have affected the hydrologic functioning of the SRD and the sedimentation patterns (Pietroń et al., 2017) that may be potentially observed through changes in its surface water extent. I employed an accurate supervised classification of Landsat-4,5,7,8 images within the period 1987-2020 to quantify surface water extent, its temporal variations, and the potential drivers of change.

### 1.1.2 Remote sensing of water levels

Satellite altimeters were initially designed to estimate marine geoid and measure sea level. Later, technological advances enabled the measurement of water levels in lakes and rivers using these satellites (Abdalla et al., 2021; Nielsen et al., 2022). The monitoring of inland water levels from space started in the 1970s with the NASA altimeter satellites SKYLAB, GEOS-3, and Seasat, primarily focused on large water bodies such as the Florida Everglades wetland and The Great Lakes in the United States (Berry et al., 2005; Brown, 1977; Miller, 1979; Rapley et al., 1987). Satellite radar altimeters transmit and receive electromagnetic microwave signals toward the water surface, and by measuring its two-way travel time, they estimate the distance between the satellite and the water surface. This distance measurement is important for determining water levels and water level changes through repeat measurements.

The technology of altimetry and the related processing methods have evolved significantly over time, leading to higher spatial resolution (300 m footprint) with SAR sensors (e.g., Sentinel-3; Villadsen et al., 2016) and high-frequency signals with less ionospheric errors (e.g., SARAL; Bonnefond et al., 2018; Verron et al., 2021). Moreover, new satellites such as Sentinel-3 are equipped with auxiliary elevation data leading to higher accuracy of water body detection (especially for small lakes) and ultimately higher quality water levels (Biancamaria et al., 2018). These advancements have led to the development of the newly launched Surface Water and Ocean Topography (SWOT) mission, which has recently started to monitor the water levels of more than 95% of all continental waters with a high degree of precision (Nair et al., 2022).

Altimetry satellites, during several orbits around the Earth, monitor the lakes falling perpendicularly below their sensor's Line Of Sight (LOS; Frappart et al., 2021). However, there are long gaps between altimetry orbits (i.e., ground track gaps > 35 km in Sweden) that leave many lakes undetected. Moreover, in small lakes with only one ground track, the temporal resolution of observations is equal to the revisit time of the altimeter satellite ( 10-35 days; Nielsen et al., 2022). To improve the temporal resolution of altimetry water levels, previous studies have implemented altimetry data from multiple satellites to get more altimetry ground tracks over a lake (Boergens et al., 2017; Pham-Duc et al., 2022; Tourian et al., 2016). Although satellite altimetry for water level estimation has the potential to partially contribute to comprehensive lake water level monitoring, with a total of 13 satellite missions since 1985 (Abdalla et al., 2021; Shu et al., 2021), there are still insufficient water level change studies in Sweden; a country with a large number of lakes.

Regarding water levels, I concentrated on lakes located in Sweden due to their critical function in supplying freshwater for urban, agricultural, and industrial purposes, in addition to serving as terrestrial and aquatic habitats for diverse flora and fauna. Sweden has 100,000 lakes covering nine percent of its surface area (Larson, 2012). Yet, today, there is no study that comprehensively assesses the water level changes of these lakes and there is a lack of information regarding the seasonal and long-term variations in water levels and their drivers. Addressing these questions can help to fill the knowledge gap regarding the effects of climate change and human influence on Swedish water resources. Furthermore, there is a lack of data on in-situ water levels as only 38 of the Swedish lakes (< 0.04%) have long and continuous gauged water level measurements. On the contrary, with satellite altimetry (old and new sensors), we can monitor the water level of a larger number of these lakes.

To tackle the challenges posed by low-resolution lake water level data in the spatial domain and the concomitant lack of information on water level changes and potential drivers, I used satellite altimetry data to increase the number of Swedish lakes with water level observations from 38 to 144 (<0.15%), allowing for improved analysis of trends and variability in water levels, as well as an assessment of potential climatic or anthropogenic factors that could be attributed to these changes. The findings from this analysis can offer critical insights into the status of Swedish water resources of use to the Swedish Meteorological and Hydrological Institute (SMHI), among other stakeholders, to safeguard the Swedish lake system against potential changes and establish appropriate policies and actions in response.

Although satellite altimetry has the potential to answer hydrologic questions regarding lake water level variations, its intrinsic limitations lead to a low temporal resolution, particularly over small lakes with only one ground track.

Alternatively, Differential Interferometry of SAR images, known as D-InSAR, is a viable tool for measuring water level changes across water bodies (Jones et al., 2021; Liu et al., 2020; Oliver et al., 2022; Palomino et al., 2022). D-InSAR calculates the phase difference between two SAR images (i.e., by generating an interferogram) to estimate water level changes after removing the effects of topography, and radar imaging geometry among other error sources. This approach can provide a high density of data points and an in-depth assessment of water level variations across broad areas. However, the D-InSAR methodology, so far, has mainly been applied to water bodies covered with dense emergent vegetation. For example, Alsdorf et al. (2000), which is the first study on the use of water level detection in wetlands with D-InSAR (mission SIR-C; Shuttle Imaging Radar with payload C), detected continuous phase changes of the long-wavelength L-band signal (24 cm) over flooded forests and floodplain lakes covered with vegetation near the Amazon River. Due to the long wavelength, they could detect water level changes of 11 cm during the 24 hours between the two acquisitions (Alsdorf et al., 2000). Wdowinski et al. (2004, 2008) applied the D-InSAR method to the wetlands of Florida Everglades to estimate water level changes, and Kim et al. (2009) and Jones et al. (2021) used D-InSAR in Louisiana wetlands. Although short-wavelength radar cannot penetrate dense vegetation such as mangroves, it can be used in wetlands with marsh and short shrubs. For example, Chen et al. (2020) employed short wavelength SAR images (C-band; $\lambda$ = 5.6 cm) from Radarsat-2 and Sentinel-1 in the marsh-dominated wetlands of Lake Erie in Ontario, Hong et al. (2010) used Radarsat-1 C-band SAR data over Florida Everglades wetlands, and Oliver and Wdowinski (2016) used long-wavelength (L-band; $\lambda$ = 24 cm) ALOS together with C-band Radarsat-1 over the Louisiana Coastal Wetlands. Wetland InSAR uses interferograms over the water surface with emergent vegetation and obtains a continuous phase change with high coherence over those surfaces. Coherence is a unitless measure of interferogram quality, ranges between zero (only noise) and one (only signal), and is helpful in detecting pixels with strong backscattering (Aminjafari, 2017). As the interferogram phase is wrapped between $\pm\pi$, all the wetland D-InSAR studies unwrapped the interferograms by counting the phase change between adjacent pixels to obtain the relative water level change w.r.t a reference pixel (Oliver et al., 2022; Yuan et al., 2017). Due to phase unwrapping, the water level change derived from D-InSAR in wetlands is relative in space unless there is a ground point measurement of the water level.

As there is no continuous vegetation cover around a lake, D-InSAR is not commonly applied to open bodies of water due to the discontinuity of sporadic pixels which does not allow the process of phase unwrapping. There is only one study focusing on lakes without emergent vegetation over the surface of the water (Palomino et al., 2022). Palomino et al. (2022) used D-InSAR with Sentinel-1 images over the mountainous lakes of Ecuador to investigate water level changes. Nevertheless, they did not have in-situ water levels for validation and were only able to compare their results with precipitation patterns. Therefore, there is a need to evaluate the performance of D-InSAR in detecting small water level changes (less than the distance equivalent to a full cycle of SAR signal) without unwrapping the phase.

## 1.2 Thesis Objectives

Regarding the challenges to understanding the temporal variation in surface water extent and levels, this thesis addresses three over-arching objectives (Figure 2 and Table 1). The first two objectives relate to a hydrologic analysis of water extent and water levels by applying satellite optical imagery and radar altimetry, and the third objective seeks to tackle remote sensing methodological challenges of D-InSAR application for water level estimation. Figure 2 illustrates the structure of this thesis based on the objectives' categories (hydrologic analysis or method development) and the type of satellite sensors (radar or optical) employed in the methodology of each paper. The study area of the first paper is the Selenga River Delta, situated in East Siberia, and the three subsequent papers focus on Swedish lakes (Figures 1 & 2).

### 1.2.1 Objective A

The first objective of this thesis is to quantify changes in surface water extent in the Selenga River Delta and water levels in Swedish lakes in the last three decades. Surface water extent and water levels inform the changes in the volume of water within the water systems. Furthermore, surface water extent provides crucial data on the changes in the structure and configuration of the Selenga River Delta and variations in sedimentation patterns that have not been thoroughly and accurately studied before with local or global datasets.

In the case of the Swedish lake system, this thesis, for the first time, focuses on a large dataset of lake water levels (144 lakes) derived from satellite altimetry and in-situ measurements to see the long-term and seasonal water level variations.

### 1.2.2 Objective B

The second objective of this thesis is to understand the principal factors responsible for the changes observed when addressing objective A. Understanding the relationship between hydroclimatic variables and water extent and water level changes can partly contribute to this objective. First, I aim to compare changes in surface water extent in the SRD with those in river discharge, sediment discharge, evapotranspiration from the delta, and Lake Baikal water levels. Second, finding differences in water availability between regulated and unregulated lakes could lead to additional insights into objective B by confirming the large-scale hydrologic effects of regulation. In the case of the Swedish lakes, I compared water level trends and variabilities with trends and variabilities in precipitation and temperature and the lakes' regulatory regimes.

### 1.2.3 Objective C

The third objective entails the development of novel remote sensing methodologies for estimating lake water levels and their changes. It aims at obtaining high-temporal-resolution observations for lakes of various sizes using D-InSAR. Such a goal can support achieving objectives A and B. I specifically used Sentinel-1A&B SAR images. To meet objective C, I first employed a D-InSAR methodology to test if the phase differences between SAR images can estimate small changes in the water levels of some lakes. Then, I assessed whether the accumulated phase changes over a large set of lakes could estimate the direction or even the magnitude of water levels, despite the limitations of D-InSAR.

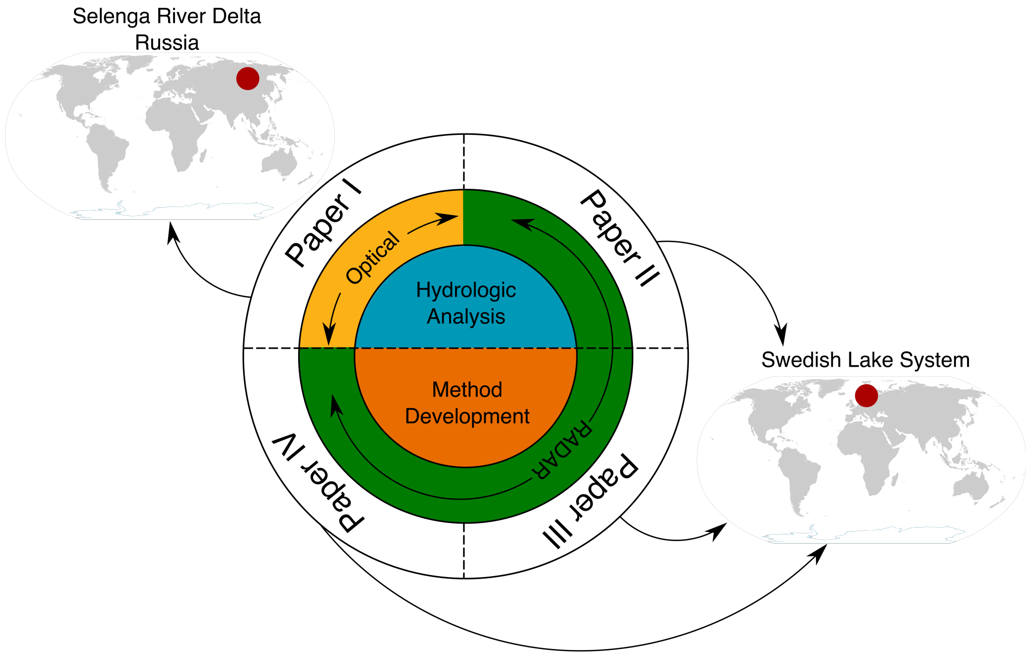


Figure 2. The thesis is structured based on three objectives in four papers. The objectives relating to hydrologic analysis are denoted in blue, and the objective relating to method development is denoted in orange. The color yellow indicates the utilization of optical sensors in the methodology, while the color green indicates the use of radar remote sensing.

Table 1. The three objectives of the thesis (A-C). The blue cells represent papers with hydro-logic analysis objectives, and the orange cell represents papers with the method development objective.

| | Objective | Type | Paper I | Paper II | Paper III | Paper IV |
|---|---|---|---|---|---|---|
| **A** | To quantify surface water extent, water levels, and their changes | Hydrologic analysis | ✓ | ✓ | | |
| **B** | To analyze the drivers of changes in surface water extent and water levels | Hydrologic analysis | ✓ | ✓ | | |
| **C** | To improve methods of water level change measurements | Method development | | | ✓ | ✓ |

# 2 Methods

## 2.1 Surface water extent

In Paper I, I used Landsat 4-5/TM, 7/ETM+, and 8/OLI imagery from 1987 to 2020 to map the surface water extent in the SRD. The Normalized Difference Vegetation Index and Normalized Difference Water Index were used to calculate image spectral indices (McFeeters, 1996), and the Maximum Likelihood supervised classifier (Guo et al., 2017) to distinguish water and non-water pixels. Training data was selected by visual inspection of Google Earth's historical view, obtaining an overall classification accuracy higher than 98%. The binary classification for 87 cloud-free and ice-free images during 33 years resulted in binary images containing two classes of pixels: water (equals 1) and non-water (equals 0).

Surface water occurrence is defined as the presence of water at a specific location on the surface and particular time, and is calculated as the average of the binary values of all images for every pixel, leading to a final value between zero and 100. This value for each pixel represents the probability that water is detected on that pixel for 33 years. The mean magnitude of change in water occurrence at each pixel between two 16-year periods (1987–2002 and 2003–2020) is also calculated by subtracting the water occurrence in the first period from that in the second. The change in water occurrence ranges from -1 (no water in any binary image in the second period and water in all binary images in the first period) to +1 (water in all binary images in the second period and no water in any binary image in the first period). Hence, negative and positive values correspond to decreasing and increasing water occurrence.

For validation, one binary image in this study, from June 2011, was compared to the binary image in a study by Berhane et al. (2018) derived from the supervised classification of a 2 m-resolution Worldview-2 satellite image. Furthermore, the change in surface water extent in the SRD is compared to global-scale datasets from studies by Donchyts et al. (2016) and Pekel et al. (2016).

Finally, the Selenga River surface runoff (RO), the water level in Lake Baikal, the suspended sediment concentration of the Selenga River (SSC), and potential evapotranspiration over the delta were compared to changes in surface water extent. The Russian Federal Service for Hydrometeorology and Environmental Monitoring (Roshydromet) provided river discharge data and SSC. The potential evapotranspiration data for the region of the SRD was derived from the 0.5° by 0.5° gridded data sets of the Climatic Research Unit (Harris et al., 2020). For Lake Baikal's water level, I used two gauge stations of the International Data Centre on Hydrology of Lakes and Reservoirs (HYDROLARE; available at: http://hydrolare.net/catalogue.php) and processed satellite-altimetry water-level data from the HYDROWEB service (available at: https://hydroweb.theia-land.fr; Crétaux et al., 2011).

## 2.2 Satellite altimetry for lake water level estimations

In Paper II, I used satellite radar altimetry to estimate water levels in Swedish lakes. Radar altimeters measure the distance between the satellite and the water surface (i.e., $Rg$ based on the two-way travel time of an emitted microwave signal between the satellite and the Earth's surface. The geodetic height of a lake water surface ($h_A$) is the difference between the height of the satellite ($H_s$) and the measured $Rg$ after applying atmospheric and geophysical corrections. The atmospheric corrections are attributed to different speeds of electromagnetic waves through the ionosphere ($C_{ion}$) and the dry and wet components of the troposphere ($C_{dry}$, and $C_{wet}$). The geophysical corrections are the Earth's crustal movements caused by the solid-Earth and pole tides ($C_{solidEarth}$ and $C_{pole}$) and the geoid height ($G_h$) given by the Earth Gravitational Model 2008 (Frappart et al., 2021):

$$h_A = H_s - Rg + C_{ion} + C_{dry} + C_{wet} + C_{solidEarth} + C_{pole} - G_h \quad (2.1)$$

As the Radar signal from inland water bodies is mixed with the signal from the surrounding land, the data from the Offset Center of Gravity retracking algorithm is used to filter land-contaminated signals (Frappart et al., 2006). On each epoch of altimetry measurements, the satellite sends a bundle of radar beams to illuminate a footprint below the satellite, and all the reflected beams from the water surface are received by the satellite. Therefore, there are several observations on each epoch of altimetry measurements. From all of the observations on each epoch, those not falling within the range of $\pm 2\sigma$ are detected as outliers and removed from the observations. The median of the remaining measurements was used as the water level value on each epoch. To assess the accuracy of altimetry-derived water levels, I compared the altimetry estimations with in-situ measurements in two lakes (Lake Hjälmaren and Lake Vättern). Paper II used data from the following satellite altimetry missions: European Remote-Sensing Satellite (ERS-2), Environmental Satellite (ENVISAT), Joint Altimetry Satellite Oceanography Network (JASON-1,2,3), Satellite with ARgos and ALtika (SARAL), Sentinel-3A, and Sentinel-3B.

To synthesize water level variations and understand the hydrologic regime in each lake, I estimated the mean annual Dynamic Storage (DS; the average of yearly maximum minus yearly minimum) and the DS annual trend with the Theil-Sen trend estimator. I calculated the long-term yearly, spring, summer, and autumn water level trends for each lake and period by the Theil-Sen trend estimator. The Theil-Sen trend of a time series is the median of all slopes between every possible pairwise combination of data points (Kraemer et al., 2020).

## 2.3 D-InSAR for water level change estimation in lakes

Similar to Radar altimetry, SAR images have a phase component related to the distance between the satellite and the surface of the Earth. However, contrary to Radar altimetry, SAR has a side-looking geometry. The pixel-based difference between two SAR images taken at two different times ($\Delta\phi$) carries information on the change in the surface displacement between the acquisition times ($\Delta\phi_{disp}$), Earth's topography ($\Delta\phi_{topo}$), the geometry of the radar imaging ($\Delta\phi_{geo}$), and the atmospheric delay and the transmitter's noise ($\Delta\phi_{other}$) (Ferretti et al., 2007):

$$\Delta\phi = \Delta\phi_{disp} + \Delta\phi_{topo} + \Delta\phi_{geo} + \Delta\phi_{other} \quad (2.2)$$

D-InSAR is the process of calculating the phase difference between two SAR images ($\Delta\phi$) and removing all the components except for $\Delta\phi_{disp}$. Therefore, $\Delta\phi_{disp}$ if obtained over water bodies, is equivalent to changes in the water level. A Digital Elevation Model (DEM) and orbital information of the satellite during acquisition time are used to remove the components of $\Delta\phi_{topo}$ and$\Delta\phi_{geo}$, respectively (Darvishi et al., 2021). The component of noise and atmosphere ($\Delta\phi_{other}$) can be reduced by applying filtering methods (e.g., Goldstein filter; Sun et al., 2013) and atmospheric models (Xiao et al., 2022; Yunjun et al., 2019).

For open water bodies such as lakes, the SAR signal can have three different interactions with the water surface (Figure 3):

1. When there is no vegetation on the water's surface or near the shore, the signal is mirrored in the opposite direction of the satellite's LOS and is not received by the satellite.

2. In the case of emergent vegetation covering the water surface (e.g., mangrove or marsh-type wetlands), the SAR signal bounces first on the water and then on the vegetation stems, and finally, is received by satellite. This so-called double-bounce backscattering generates high-intensity pixels in SAR images.

3. When there is stable vegetation surrounding a lake (e.g., lakes in forested areas), there are high chances of double-bounce backscattering near the shore.

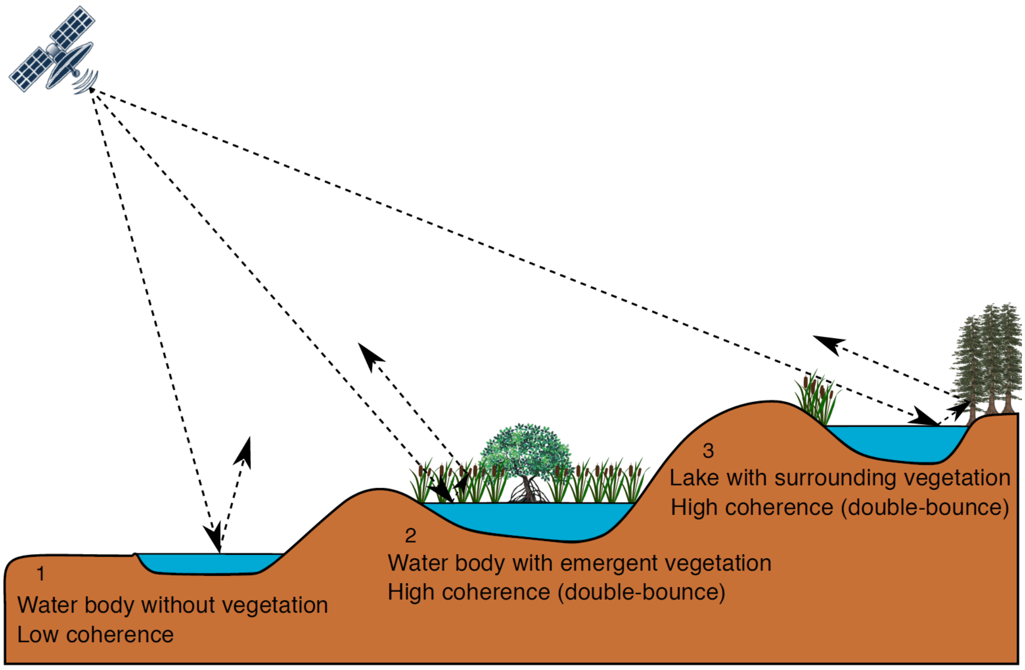


Figure 3. Three different types of interaction of the SAR signal with water bodies and vegetation. Figure is from Paper III and Paper IV.

In Swedish lakes, case numbers two and three are very likely to happen with high-intensity pixels near the shorelines of the lakes. Therefore, Papers III and IV focus on these areas.

To estimate water level change, I used the combination of Sentinel-1A and Sentinel-1B in 2019 to generate the shortest temporal baseline interferograms (every six days) with the smallest changes. I chose a potentially stable reference point near the lakes (e.g., buildings and car parks) and subtracted its phase change from that of the other pixels, and performed the analysis within a 1 km distance from the reference point to minimize atmospheric delays. Since D-InSAR cannot detect changes exceeding the distance equivalent to a full cycle of the SAR signal, I used in-situ measurements to identify the instances of such large changes and removed them from the analysis. Finally, I compared the time series of phase change with the in-situ water level changes and calculated Lin's Concordance Correlation Coefficient (CCC) between them (Akoglu, 2018).

The procedure in Paper IV is similar to the methodology in Paper III; however, I kept all of the interferograms, even those corresponding to water level changes exceeding the distance equivalent to a full cycle of the SAR signal. This is to determine if, with a large sample of lakes, the general long-term trend of water level in the lakes can be predicted. This paper accumulated the water level changes of the pixels with high coherence ($> 0.25$) sequentially, starting from the first interferogram to the last one (without the pre-knowledge of the actual water level changes). However, since D-InSAR alone can estimate the magnitude of water level changes only if the actual water level changes are less than the distance equivalent to a full cycle of the SAR signal, Paper IV tested if the long-term direction of change in water level (instead of the magnitude) can be estimated by D-InSAR despite the rapid water level changes.

# 3 Results

## 3.1 Objective A

### 3.1.1 Paper I

This paper aimed to analyze the water occurrence and its changes in the SRD from 1987-2002 to 2003-2020. The changes in surface water occurrence in the SRD generally point to drying of the delta; however, they are relatively small and often fall within the range of ±20% (Figure 4a). Furthermore, 51% of the spatial extent of the SRD experienced a decreasing water occurrence and predominantly in seasonally flooded regions rather than in areas covered permanently with water (Figure 4b).

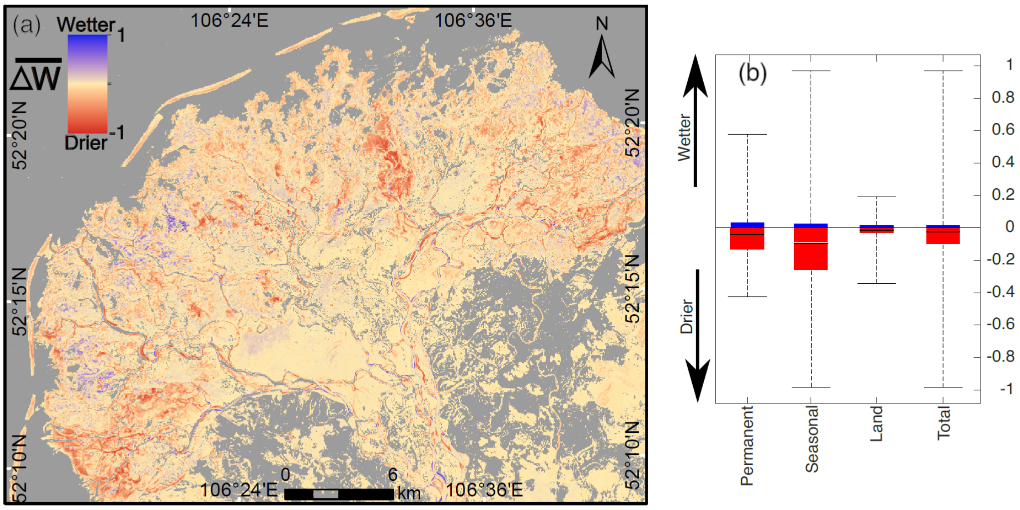


Figure 4. **(a)** Change in surface water occurrence ($\overline{\Delta w}$) between 1987-2002 and 2003-2020 for pixels with $\overline{\Delta w} \neq 0$. Red areas (-1) show losses of water surface, and blue areas gains (+1), **(b)** Pixel distributions of $\overline{\Delta w}$ by general categories (i.e. permanent water, seasonal water, and land). Figure is modified from Paper I (Aminjafari et al., 2021).

### 3.1.2 Paper II

This paper aimed to estimate water level trends in 144 Swedish lakes. Around 52% of lakes studied here showed statistically significant increasing trends in water levels, and 43% exhibited statistically significant decreasing trends from 1995 to 2022 (Wilcoxon rank sum test, $p < 0.05$, large circles; Figure 5a). Most of the decreasing trends occur in the south and most of the increase in the north of Sweden. During a shorter period (2013-2022) with more lakes, I observed similar patterns of water level trends, with 53% of them showing increasing water levels (mainly in the north) and 24% of them decreasing (mostly in the south; Figure 5b).

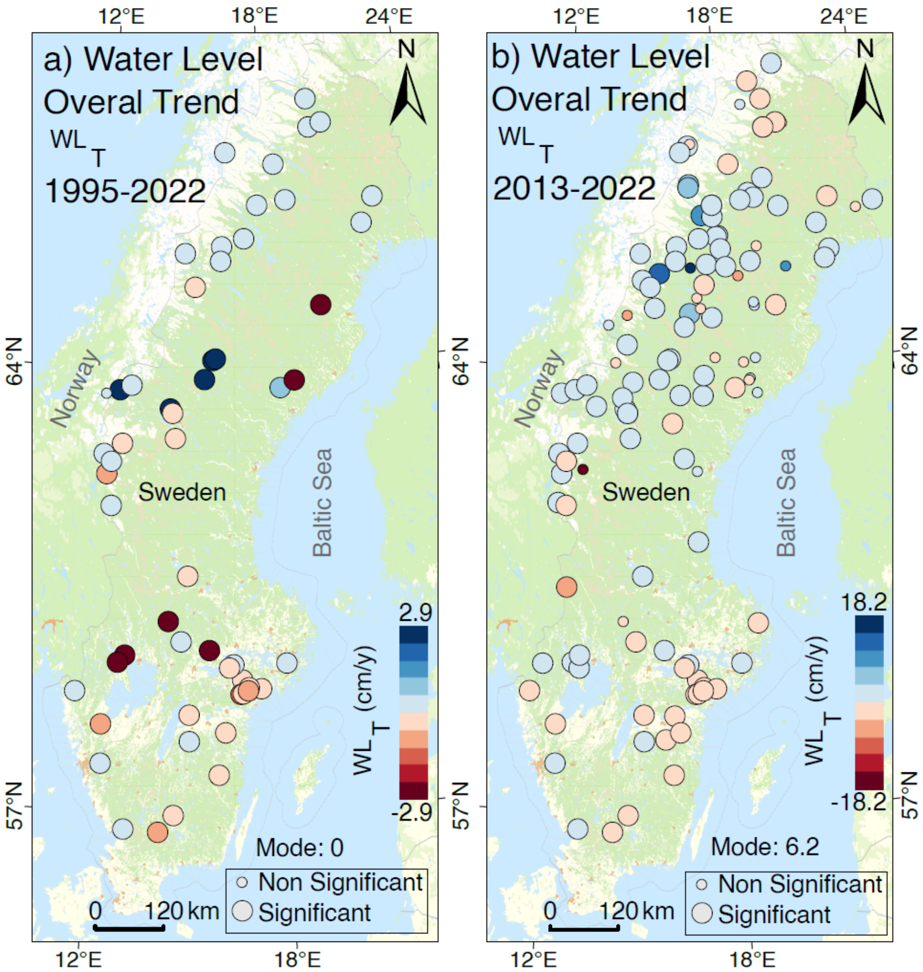


Figure 5. Water level trends $WL_T$ from both altimetry and gauges **(a)** from 1995 to 2023 in 58 lakes with all available altimetry sensors and **(b)** from 2013 to 2022 in all 144 lakes. Large circles show a significant trend (Wilcoxon rank sum test; p-value < 0.05). Blue implies a positive trend, whereas red a negative trend. Figure is modified from Paper II.

## 3.2 Objective B

### 3.2.1 Paper I

This paper aimed to determine the possible drivers of the change in water occurrence. At the center of the SRD (Figure 1a), there is a significant positive correlation (p-value < 0.05) between the temporal patterns of surface water occurrence and RO. On the other hand, changes in SSC, lake water levels, and potential evapotranspiration do not significantly correlate with changes in surface water occurrence (Table 2).

Table 2. Statistics of the linear regressions between the time series of surface water occurrence ($\overline{w}_s$) and RO, SSC, water level (WL) in Lake Baikal, and potential evapotranspiration (PET) in the central part of the SRD (Figure 1a). I selected RO data on the images' acquisition days, SSC with a 2-week delay, the Lake water level data nearest to the image acquisition date, and PET in the same month. Numbers in bold denote significant positive correlations. Table is modified from Paper I (Aminjafari et al., 2021).

| | $R^2$ | p-value |
|---|---|---|
| $\overline{w}_s$ vs. RO | **0.58** | **<0.05** |
| $\overline{w}_s$ vs. SSC | 0.01 | 0.7 |
| $\overline{w}_s$ vs. WL (Altimetry) | 0.06 | 0.03 |
| $\overline{w}_s$ vs. PET | 0.01 | 0.28 |

### 3.2.2 Paper II

This paper aimed to determine how the regulatory structure of the 144 Swedish lakes and climatic variables can affect water level trends and DS. The trend in water levels, and DS, of non-regulated lakes (N) are significantly different (Wilcoxon rank sum test, p-value < 0.05) from those in regulated lakes (i.e., with direct regulatory structures (R) or upstream regulatory regimes (U; Table 3). This means that the population of water level trends and DS in non-regulated lakes have a different distribution with a different median than the population of water level trends and DS in regulated lakes.

Table 3. P-values of the Wilcoxon rank sum test between pairs of lake water level trends ($WL_T$) and mean annual Dynamic Storage (DS) with four regulatory structures: non-regulated lakes (N), upstream regulatory regimes (U), regulated lakes (R), and lakes subjected to both upstream and direct regulatory structures (R+U). Astrix denotes those values with statistically significant differences. Table is from Paper II.

| $WL_T$ | **N** | **U** | **R** | **R+U** |
|---|---|---|---|---|
| | **N** | 0.001** | 0.06** | 0.26 |
| | | **U** | 0.83 | 0.16 |
| | | | **R** | 0.34 |
| | | | | **R+U** |

| $DS$ | **N** | **U** | **R** | **R+U** |
|---|---|---|---|---|
| | **N** | 0.01** | 0.08** | 0.05** |
| | | **U** | 1 | 0.86 |
| | | | **R** | 0.78 |
| | | | | **R+U** |

On the other hand, I did not observe a strong Pearson's correlation (Pc > 0.7) between water level trends (or DS) and climatic variables (precipitation and temperature) in any regulation lake category (N, U, R, R+U; Figure 6).

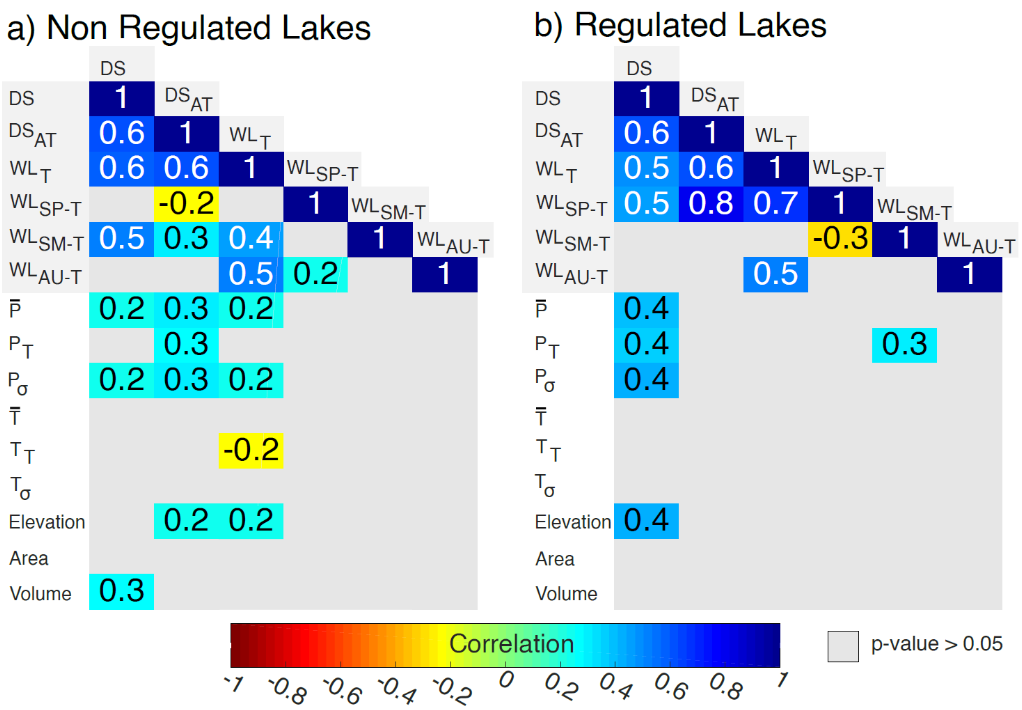


Figure 6. Pearson's correlation matrix in **(a)** non-regulated lakes and **(b)** regulated lakes (U, R, and R+U) between DS, water level trends (overall $WL_T$, spring $WL_{SP-T}$, summer $WL_{SM-T}$, and autumn $WL_{AU-T}$), precipitation (average $\overline{P}$, trend $P_T$, and standard deviation $P_\sigma$), temperature (average $\overline{T}$, trend $T_T$, and standard deviation $T_\sigma$), lake elevation, lake surface area, and lake volume during the period 2013 – 2022. The numbers inside the cells and the color bar show the correlation values. Gray cells are not significant, and colored square values are significant (Pearson's p-value < 0.01). Figure is from Paper II.

## 3.3 Objective C

### 3.3.1 Paper III

This paper aimed to evaluate the performance of D-InSAR in estimating small changes in lake water level. The two lakes studied in Paper III, Lake Hjälmaren and Lake Solnen, are located in southern Sweden (Figure 7a) and have historically small water level changes (Figure 7b, e). I generated 17 and 34 interferograms for Lake Hjälmaren and Lake Solnen, respectively, corresponding to occasions when the water level changes between consecutive dates were smaller than the distance equivalent to a full cycle of the SAR signal (Figure 7b, e). Focusing on small areas near lake shores, I detected forested vegetation cover in Lake Hjälmaren and emergent vegetation (marsh-type wetland on the surface) in Lake Solnen, which create a double-bounce backscattering (Figure 3) evident in the SAR images (Figure 7d, g). The high average coherence of the pixels in these areas is most probably attributed to the double-bounce backscattering (Figure 7c, f). In Lake Solnen, pixels with higher mean coherence show higher CCC with in-situ water level changes (Figure 7d, g).

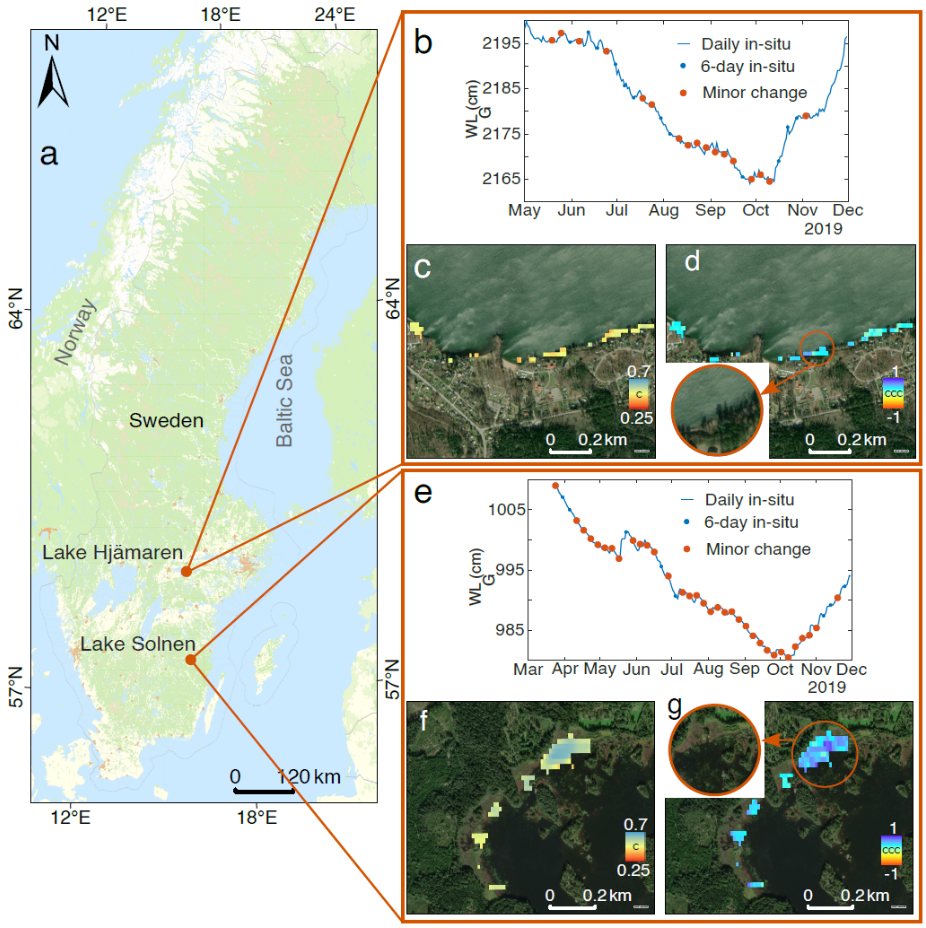


Figure 7. **(a)** The location of the two lakes in Southern Sweden with small six-day water level fluctuations. **(b)** The time series of daily in-situ water levels ($WL_G$), orange dots denote the occasions that six-day water level changes are smaller than the distance equivalent to a full cycle of the SAR signal, **(c)** the average coherence of all interferograms (C), and **(d)** CCC between D-InSAR- and in-situ water level change for Lake Hjälmaren. **(e to g)** $WL_G$, C, and CCC for Lake Solnen respectively. The circle in panels d and g denotes an area with high CCC. Figure is from Paper III.

CCC between D-InSAR- and gauged water level change ($\Delta WL_D$ and $\Delta WL_G$) can be as large as 0.63 and 0.89 in Lake Hjälmaren and Lake Solnen, respectively, equivalent to Root Mean Square Errors (RMSE) of 0.92 and 0.43 cm (Figure 8). This shows that D-InSAR can potentially detect water level changes in some ungauged lakes.

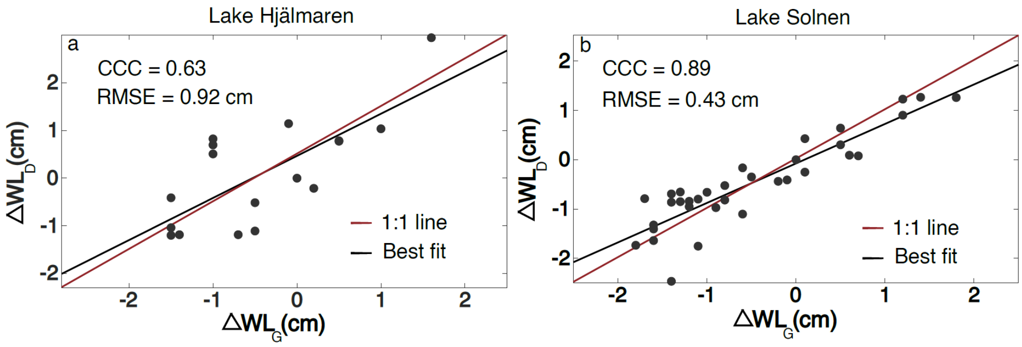


Figure 8. Correlation between D-InsAR water level change ($\Delta WL_D$) and gauged water level change ($\Delta WL_G$) for the pixel with the highest CCC in **(a)** Lake Hjälmaren and **(b)** Lake Solnen. Figure is modified from Paper III.

### 3.3.2 Paper IV

This paper aimed to test the methodology employed in Paper 3 over a larger sample of Swedish lakes (30 lakes) to estimate the direction of change in water levels. Here, I used Pc and CCC to compare the derived D-InSAR water levels ($WL_D$) with gauged water levels ($WL_G$). The study finds that there are, in fact, pixels within the lakes that show a high Pc between water level anomalies based on gauged observations and D-InSAR phase changes, proving that the method can eventually determine the direction of the change in water level (i.e., increase or decrease).

The high Pc between $WL_D$ and $WL_G$ is found mainly in Southeast Sweden (Figure 9a). On the other hand, CCC is low, especially in northern Sweden (Figure 9b), which is expected as the method includes water level changes beyond the distance equivalent to a full cycle of the SAR phase. It is worth noting that the pixels with the highest Pc are located near the shoreline and surrounded by wetlands and forests. It is possible that some of these pixels were indeed located onshore rather than in the lake itself, and lake water level variations could have influenced the surrounding land, resulting in the observed correlation. This may be due to the poroelastic soil responding to changes in water levels.

Therefore, the pixel-specific D-InSAR method can determine the direction of water levels between consecutive acquisitions but not the exact magnitudes of water levels, as most changes extend beyond the distance equivalent to a full cycle of the SAR phase (Figure 9).

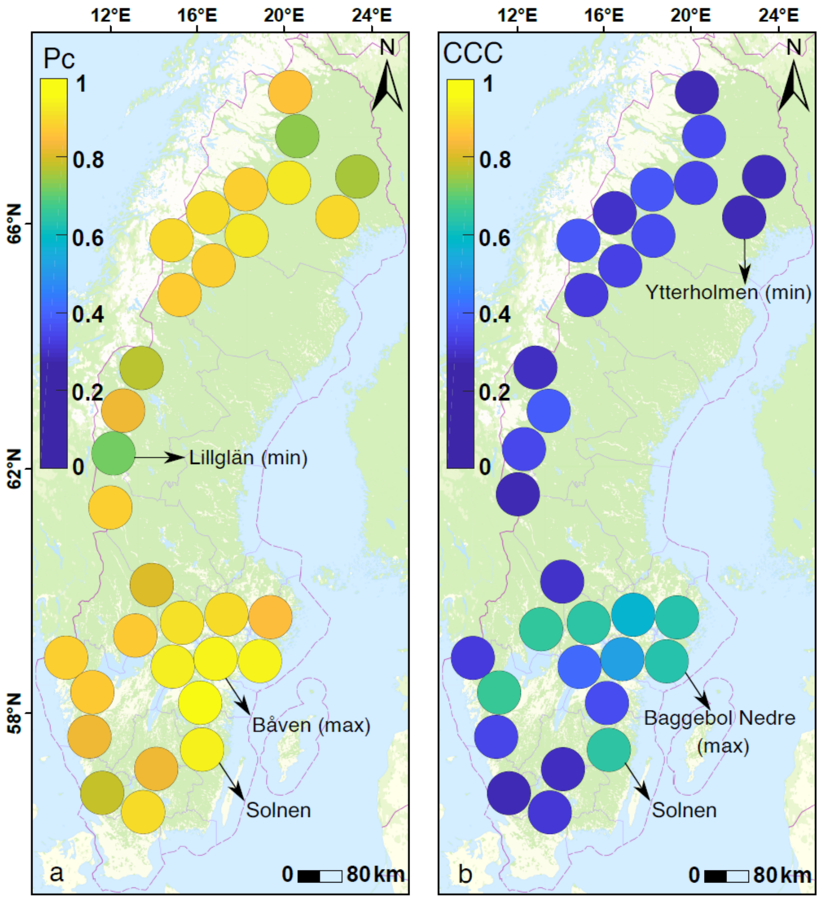


Figure 9. The relationship between gauged- and D-InSAR-derived water levels **(a)** Pearson's correlation coefficient (Pc) showing if the direction of the change in water level is estimated and **(b)** Lin's Concordance Correlation Coefficient (CCC) showing if the magnitude of water level is estimated. Figure is modified from Paper IV.

# 4 Discussion

## 4.1 Objective A

The findings in Paper I showed that during the last 33 years, the SRD experienced a decrease in surface water occurrence in 51% of its surface area. The rest of the delta exhibited no change (30%) or an increase (19%). The dominant decrease in surface water occurrence agrees with the decreasing water occurrence pattern in northern Siberia observed by Borja et al. (2020). However, on larger scales, water occurrence varies across regions characterized by diverse hydrologic and geomorphologic conditions. For example, two different wetlands in Turkey show contradicting trends in water occurrence during the same period, although being neighbors (Dervisoglu, 2022).

Within the scope of quantifying changes in surface water occurrence, Paper I demonstrated its ability to identify planform migrations and oxbow lake formations based on the change in water occurrence, setting Paper I apart from other related studies (such as Chen et al., 2020; Dervisoglu, 2022; Donchyts et al., 2016; Pekel et al., 2016). The changes in river planforms in deltas can be detected from individual satellite images (such as Yuan et al., 2022); however, they are only snapshots of the tributaries, while the maps of surface water occurrence and its changes exhibit the percentage (or probability) and the growth of a newly formed path, drying path, or an oxbow lake formation. The in-channel processes can further complement in-situ geomorphological data of bedload variations and changes in the shape of a delta.

Quantifying surface water occurrence in deltas and wetlands with satellite images has a certain level of uncertainty associated with the presence of water below vegetation. For example, in Paper I, with the utilization of Landsat optical images, the water beneath a dense vegetation canopy in the forested areas remains undetected, leading to two distinct patterns of water occurrence. Firstly, in areas with perennial vegetation, hidden water below the vegetation leads to a detected water occurrence that is lower than the actual water occurrence. Secondly, in areas with deciduous vegetation, the hidden water beneath the vegetation causes the detected water occurrence during leaf-off seasons to represent the actual water occurrence. In contrast, the detected values are lower during leaf-on seasons. Some studies compensated for the limitation of optical images in detecting water below vegetation by incorporating radar images (Chen and Zhao, 2022; Li and Niu, 2022; Tottrup et al., 2022). However, most of these studies have used short-wavelength SAR images, which cannot penetrate thick tree canopies. This challenge can be mitigated using L-band sensors such as ALOS PALSAR, ALOS PAL-SAR-2, and soon, the long wavelength dual-frequency NISAR mission. The NISAR satellite is equipped with SAR sensors operating in both S-band (7.5-15 cm wavelength) and L-band (15-30 cm wavelength), which enables the detection of water beneath vegetative cover, providing an enhanced capability to observe and analyze water resources.

Similar to variations in surface water occurrence in deltas, lake water level changes have implications for water supply management and the ecological well-being of the biota inhabiting them and their surrounding environments. Therefore, the common motivation for quantifying changes in water level is to provide insights into water management and restoration strategies. These strategies aim to enhance the adaptation of the ecosystem to the dynamic changes in water levels, with the ultimate goals of improving hydrologic connectivity to increase water circulation, mitigating water salinity issues, and achieving sustainable water consumption practices (e.g., Dersseh et al., 2020; Ren et al., 2019; Saber et al., 2020; Schulz et al., 2020).

Regarding water levels, I could estimate water level trends and variability in 144 lakes in Sweden using satellite radar altimetry data, doubling the number of lakes with current in-situ observations. With laser altimeter satellites such as ICESat-2, it is possible to monitor even more lakes due to shorter gaps between satellite ground tracks; however, with coarser temporal resolutions (e.g., Cooley et al., 2021).

In addition, current altimetry sensors could complement upcoming missions. For instance, water levels from laser and radar altimeters can help validate and cross-compare the data from the newly-launched SWOT mission that covers 95% of all inland water bodies globally. SWOT, a collaborative mission by NASA, the French Space Agency (CNES), the Canadian Space Agency (CSA), and the UK Space Agency (UKSA), provides more than four observations within each 21-day repeat cycle in high latitudes, enhancing our understanding of water level variations as well as water storage (Crétaux et al., 2015; Yoon et al., 2016).

Our interpretation of the total changes in lake water levels can also be more comprehensive when accounting for small lakes rather than only studying large lakes as it is done conventionally. For example, Paper II, which investigated both large and small lakes, found different water level trends compared to the study recently conducted solely on large lakes by Yao et al. (2023). They used a dataset of the 1972 largest global lakes and found that water storage in the largest lakes in high-latitude humid regions, such as Sweden, has a decreasing trend (Yao et al., 2023). This contradicts our findings in Paper II, showing an increasing trend for most lakes. The difference between the results of Paper II and those of Yao et al. (2023) may stem from two facts: 1) Yao et al. (2023) considered only lakes larger than 100 $km^2$ with the reasoning that the largest lakes account for 96% of the global lake volume and 81% of the reservoir storage; 2) Paper II estimated the trends of water levels, whereas Yao et al. (2023) estimated the trends of lake water storage. As lake water storage is calculated by multiplying the change in water level by the change in water surface extent, the trend of water storage cannot be necessarily similar to the trend of water level.

## 4.2 Objective B

Quantifying the water occurrence and level changes is merely the first step to enabling decision-making and targeted actions. In the next step, it is required to identify the potential drivers behind those changes. Most studies quantifying changes in water occurrence and lake water levels on local and global scales tried to discern the relative significance of each driver from the combined effect of all drivers. This includes investigating whether these changes are primarily attributed to direct human intervention, climate change, or a combination of both factors (e.g., Borja et al., 2020; Fan et al., 2021; Gronewold and Rood, 2019; Papa et al., 2023; Schulz et al., 2020; Woolway et al., 2020; Yao et al., 2023).

However, identifying and differentiating the sources of changes in water occurrence and water level is not straightforward. For example, the main driver of water occurrence in the central part of the SRD (Figure 1a) was surface runoff, with a weak coefficient of determination ($R^2 = 0.58$). Considering that runoff in the main tributary of a delta is the main driver of its water changes a higher correlation between water occurrence and surface runoff was expected. However, suspended sediment load and geomorphological changes in the delta can lead to delta uplift or delta sink which ultimately modify water occurrence by the formation or the sinking of islands. This was evident by the spatial variation in water occurrence corresponding to patterns in sediment aggregation and retention and the uplift of the delta found in another study (Chalov et al., 2017).

Additionally, as discussed in Objective A, since quantifying water occurrence and its changes with optical imagery has a level of uncertainty attributed to hidden water below the vegetation, accounting for hidden water may find a stronger relationship between RO and actual water occurrence in the SRD.

Moreover, Paper I did not focus on the potential anthropogenic factors such as changes in land use and water exploitation for agriculture and mining that may have affected the changes in surface water occurrence. As shown by other studies, agricultural and mining activities, on-site or upstream of a delta, can also drive changes in water occurrence (Chang et al., 2015; Chen et al., 2020; Chuai et al., 2021).

In the context of the SRD, my analysis focused solely on the unregulated nature of the Selenga River, which directly feeds into the SRD. However, it is important to note that the regulatory regime of other rivers flowing into Lake Baikal, such as the Angara River on the opposite side of the lake (Figure 1a), indirectly influences the SRD. For example, the Irkutsk dam on the Angara River has primarily impacted the fluctuations in the water level of Lake Baikal itself. Consequently, the absence of a discernible correlation between the water level of Lake Baikal and the changes in water occurrence within the SRD may relate to the complex interplay of the regulatory measures on the many other rivers flowing into the lake (Figure 1a).

Regarding Swedish lake water levels, identifying the sources of their changes is not straightforward either. Paper II classified the Swedish lakes into two broad categories: Regulated and Non-regulated. The purpose was to examine the correlation between changes in water levels and hydroclimatic variables within each category to determine if the impact of climate varies among categories. Despite this classification, no correlation was found. However, it is worth noting that the hydrologic responses of water resources to climatic changes may be more discernible when using other classifications. On a global scale, factors such as the region's general climatic and geomorphological conditions can complicate the identification of water level change drivers (Yao et al., 2023). For example, the response of lakes located in humid regions to climatic changes or anthropogenic intervention is different from those in arid regions. Yao et al. (2023) categorized global lake catchments into humid and arid regions based on precipitation rates, and Sweden is classified as a humid region. Another study has explored classifications based on regional landforms (e.g., mountains, plateaus, and plains), climate types (e.g., arid, semi-arid, and continental), and ecosystem features (e.g., forests and prairies; Heidari et al., 2020). Heidari et al. (2020) studied the impacts of climate change on all river basins in the United States and showed that aridity in mountain, plateau, and basin-type of landforms decreased over the 21st century, with basin types being more sensitive to climate change.

Paper II showed a notable distinction in the direction of water level changes. For example, northern Swedish lakes, predominantly in mountainous regions, exhibited an increasing trend in water levels. On the other hand, southern lakes, mainly located in the plains, displayed a decreasing trend. Therefore, it is plausible that by categorizing lakes according to various landforms, climate types, and ecosystem characteristics, we can identify correlations between hydroclimatic changes and water level variations within one or more of these classes.

In Sweden, the effect of climate change is not evident on lake water levels. Studies in Sweden have shown that evapotranspiration trends and runoff variability strongly depend on flow regulation (Destouni et al., 2013), agricultural development (Jaramillo et al., 2013), and forestry management (Jaramillo et al., 2018). Therefore, the lack of a strong climate change signal in lakes should not be interpreted as water resources in Sweden being unaffected.

There is a statistically significant difference between water-level trends (or DS) in regulated lakes and water-level trends (or DS) in unregulated ones (Paper II). This response of lakes to water regulation aligns with the response observed in evapotranspiration and river flow during the last century; regulated Swedish basins experienced a noticeable increase in relative evapotranspiration and a decrease in runoff variability, while unregulated basins did not display a clear trend (Destouni et al., 2013). Regarding the future, Arheimer et al. (2017) suggested that water regulation, particularly through hydropower operations, will be the main driver of river runoff in snow-fed rivers in Sweden throughout the 21st century.

The influence of water regulation extends beyond Sweden, impacting water level trends and variabilities in lakes worldwide. A notable example is the Yellow River basin in China, where reservoir operations have emerged as the primary driver of changes in terrestrial water storage (Xie et al., 2022). Even globally, 57% of the variability in surface water storage is attributed to the regulated reservoirs (Cooley et al., 2021).

## 4.3 Objective C

Paper III showed that over a dataset of six-day interferograms, the phase change of pixels that may exhibit a double-bounce backscattering of the radar signal can correlate with lake water level changes. This finding is consistent with the study by Palomino et al. (2022), which showed that the accumulated phase change of the pixels over mountainous lakes in Ecuador correlates with precipitation data. However, Palomino et al. (2022) did not have in-situ water levels to validate their results. The lakes in that study were surrounded by cliffs that probably created a suitable medium for double-backscattering. However, Paper III revealed that forest and marsh-dominated wetlands near the lakes' shores can also cause the proper conditions for a double-bounce backscattering around the lakes.

Moreover, Palomino et al. (2022) reconstructed water levels by accumulating the phase change of each pixel through the whole number of interferograms, while Paper III focused on phase changes (without accumulation) and compared those with in-situ water level changes only on occasions corresponding to a water level change that is less than the distance equivalent to a full SAR phase cycle.

Regarding the D-InSAR methodology to estimate water level changes, as explained in the Method section, there are three scenarios of radar interactions with water bodies (Figure 3). Most previous studies have focused on the second scenario, where the water body is covered by emergent vegetation, usually occurring in wetlands (Alsdorf et al., 2000; Jones et al., 2021; Kim et al., 2009; Oliver et al., 2022; Wdowinski et al., 2008; Yuan et al., 2017). However, Paper III and Paper IV focused on the third scenario of the interaction of the SAR signal with water bodies (Figure 3) occurring on the shore of lakes and surrounded by vegetation. As this scenario only relates to sporadic pixels coherent in time but not connected to the neighboring pixels and occurring at very local scales, unwrapping the phase is impossible. Hence, Paper III focused on the subtle changes in water levels in individual pixels and calculated the absolute water level change between image pairs.

Furthermore, the use of short wavelength in Paper III (C-band) can only detect subtle water level changes (2.75 cm in the LOS direction), limiting this method's applicability as lakes usually have much larger water level changes between SAR acquisitions. This challenge highlights the importance of the future NISAR mission with long wavelength (L-band; 24 cm), 12-day repeating orbit, and quad polarization in some areas (Rosen and Kumar, 2021).

Finally, it is to wonder why, despite knowing that some of the water level changes studied in Paper IV are beyond the distance equivalent to one full cycle of the SAR signal, Pc between the time series of water levels constructed from D-InSAR and observations are relatively high across some lakes. A possible explanation for this is that pixels exhibiting this high correlation may have been located on the land near the shore of the lake and not on the water, with the surrounding land responding to changes in water availability in the lake. Examples of these effects have been described in other lakes and reservoirs (Cavalié et al., 2007; Darvishi et al., 2021). The phase change may relate to the rebound of the soil around the lake originating in a poroelastic or elastic deformation with changes in water level (Doin et al., 2015; Zhao et al., 2016). These deformations would imply an agreement in the direction of change in the lake water level and the deformation of the ground surface shown by a high correlation in some lakes.

Another disadvantage is that without in-situ water level observations, it is difficult to find the pixel whose phase change best describes real water level changes. Hence, the method now relies on lakes with in-situ water levels to assess its effectiveness.

The assessment of changes in water occurrence and levels and their drivers in this thesis has greatly benefited from the utilization of remotely sensed EO. Future advancements in satellite sensors like SWOT and NISAR, coupled with innovative processing methods, have the potential to enhance our understanding of freshwater resources and the development of more effective water monitoring and management strategies.

# 5 Conclusion

## 5.1 Objective A

The findings in this thesis show that in the Selenga River Delta:

- The change in surface water occurrence ranges from -20% (water loss) to +10% (water gain), with 51% of its area experiencing a weak decrease.
- The change in surface water occurrence reveals in-channel processes (such as river planform migration and oxbow lake formations) which deliver information on the evolution of the delta structure and the stream network change.

Moreover, Paper II shows that in 144 Swedish lakes:

- Water levels in about 52% of the analyzed Swedish lakes show significant increasing trends during both 1995-2022 and 2013-2022, and in 43% of the lakes, decreasing trends. Water levels in northern lakes usually exhibit an increasing trend, and in southern lakes, a decreasing trend.

## 5.2 Objective B

In the Selenga River Delta:

- The changes in surface water occurrence correlate moderately with surface runoff ($R^2$ = 0.56) and not with suspended sediment concentration in the Selenga River, lake water levels in the outlet of the delta, and potential evapotranspiration over the surface of the delta.
- Since the values of surface water occurrence are based on the open water observed in optical images, accounting for hidden water below vegetation would possibly alter such correlation.

Paper II shows that in 144 Swedish lakes:

- There is not a strong relationship between changes in water levels and their variability and precipitation, temperature, or the physical characteristics of lakes such as lake surface area, volume, and elevation.
- There is a statistically significant difference between water level trends (or variabilities) in regulated lakes and water level trends (or variabilities) in non-regulated lakes.

## 5.3 Objective C

This thesis shows that:

- The time series of phase change in individual pixels in the Swedish lakes Hjälmaren and Solnen, correlate with the actual water level changes from in-situ measurements when these changes are smaller than the distance equivalent to a full cycle of the SAR phase.
- There is at least one pixel along the shores of the 30 Swedish lakes in which the accumulated phase change follows the direction of change in the actual water levels (increase or decrease). However, the magnitude of water levels cannot be estimated with D-InSAR as there are many occasions when water level changes exceed the distance equivalent to a full cycle of the SAR phase.

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