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Distinctive Patterns of Water Level Change in Swedish Lakes Driven by Climate and Human Regulation

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Key Points:

- Increasing lake water level trends in 52% of all lakes and decreasing in 43% of them
- Increasing water level trends in northern Sweden and decreasing in the south
- Different Water level seasonal patterns in regulated and non-regulated lakes in the South

Supporting Information:

Supporting Information may be found in the online version of this article.

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Abstract Despite having approximately 100,000 lakes, Sweden has limited continuous gauged lake water level data. Although satellite radar altimetry (RA) has emerged as a popular alternative to measure water levels in inland water bodies, it has not yet been used to understand the large-scale changes in Swedish lakes. Here, we quantify the changes in water levels in 144 lakes using RA data and in situ gauged measurements to examine the effects of flow regulation and hydroclimatic variability. We use data from several RA missions, including ERS-2, ENVISAT, JASON-1,2,3, SARAL, and Sentinel-3A/B. We found that during 1995–2022, around 52% of the lakes exhibited an increasing trend and 43% a decreasing trend. Most lakes exhibiting an increasing trend were in the north of Sweden, while most lakes showing a decreasing trend were in the south. Regarding the potential effects of regulation, we found that unregulated lakes had smaller trends in water level and dynamic storage than regulated ones. While the seasonal patterns of water levels in the lakes in the north are similar in regulated and unregulated lakes, in the south, they differ substantially. This study highlights the need to continuously monitor lake water levels for adaptation strategies in the face of climate change and understand the downstream effects of water regulatory schemes.

Plain Language Summary Energy production and water consumption have led to the regulation of many lakes in Sweden. To understand the consequences of human activities, we studied water level changes in 144 regulated and non-regulated lakes, utilizing satellite data. We found that regulated lakes show larger water level changes and variability compared to non-regulated ones. These findings underscore the need for effective adaptation strategies to mitigate the impacts of water regulatory schemes.

1. Introduction

Covering over 2% of the Earth's surface, lakes are important sources of freshwater for the agricultural and urban sectors and contribute to aquatic and terrestrial ecosystem services (Lehner et al., 2022; Zhao et al., 2022). Since climatic change and anthropogenic activities negatively impact their ecosystem functioning (Pi et al., 2022), lake water level monitoring can deliver information on the ecological status of a lake ecosystem and the drivers of change. Lake water level monitoring is necessary to understand and manage the benefits lakes provide to the environment and society (Chen et al., 2022; Kostianoy et al., 2022; Liu et al., 2022; Palomino et al., 2022). Yet, lake water level changes are often overlooked, in situ water level stations are unevenly distributed, and their number is declining worldwide due to expensive installation and maintenance and logistic difficulties, especially for small and remote lakes (Cooley et al., 2021; Oularé et al., 2022; Palomino et al., 2022; F. Xu et al., 2022).

Satellite radar altimetry (RA) is an alternative to conventional in situ gauges to measure lake water levels (Cretaux et al., 2017). The early launched satellite altimeters could only determine marine geoid and measure sea level, but now, due to technological and data processing advances, they can accurately measure periodic water levels in inland water bodies (Abdalla et al., 2021; Nielsen et al., 2022). Radar altimeters measure water levels based on the travel time of an electromagnetic wave emitted in the nadir direction and backscattered by a water surface. However, due to the nadir-looking geometry of the satellite altimetry and long gaps between satellite ground tracks, small lakes with few and short along-track passes of the satellites have a low temporal resolution of altimetry observations, that is, ≥10 days depending on the altimetry mission (Nielsen et al., 2022). Therefore, data from multiple altimetry missions can achieve higher temporal resolutions and longer time series of water levels (Boergens et al., 2017; Pham-Duc et al., 2022; Tourian et al., 2016). Moreover, new altimeter satellites such as

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Sentinel-3 and Cryosat-2 are equipped with Synthetic Aperture Radar (SAR), which provides higher along-track data resolution with a 300-m footprint (Villadsen et al., 2016), and sensors with high-frequency Ka-band signals (ARgos and ALtiKa; SARAL) that are less affected by the ionosphere, have better horizontal and higher vertical resolutions (Bonnefond et al., 2018; Verron et al., 2021). Furthermore, the altimetry sensors onboard of new satellites such as Sentinel-3 benefit from the Open-Loop Tracking command, which has auxiliary elevation data to enhance the accuracy of the window positioning and acquire high-quality observations over small lakes in mountainous areas (Biancamaria et al., 2017, 2018).

In the case of Sweden, the more than 100,000 existing lakes extend over 9% of the country's surface area and are a central component of the hydrologic cycle and ecological systems (Larson, 2012). Surprisingly, only 38 have continuously gauged water level data (mostly from 1990 to 2022), and to date, there is no comprehensive study on the variability and recent changes in lake water levels. Tracking lake water levels is fundamental to understanding the current temporal and spatial variability of water availability in lakes and their potential as freshwater sources for agriculture and communities. Although a few lakes are regulated on-site in Sweden, many receive freshwater inflows from regulated lakes or rivers upstream. Therefore, long-term observations would also help to investigate the possible effects of human regulation on recent changes in lake water levels.

To this end, we use and combine RA data from the following 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. Overall, RA data were acquired by one or several sensors over 106 lakes in Sweden from 1995 to 2022. The availability of water level data depends on the altimetry sensor as follows: 1995–2010 (ERS, ENVISAT, JASON-1,2 missions), 2013–2022 (SARAL, JASON-2,3, Sentinel-3A, B), 1995–2022 (all available missions). In addition to RA-derived water level observations, we use water level time series from 38 gauged lakes to generate a total data set for 144 lakes and analyze the annual and seasonal trends of water levels and their variability. Finally, we compare these changes with temperature and precipitation for each lake, surface area, lake type (regulated/non-regulated), elevation, and volume to differentiate the contribution of each factor to lake water level trends and variability.

2. Materials and Methods

2.1. Study Area

The Swedish Meteorological and Hydrological Institute (SMHI) operates around 60 gauge stations to record lake water levels with varying periods and continuous or interrupted time series. In this study, we use continuous daily water level data for 36 lakes during 1995–2022 and for two lakes during the shorter period 2013–2022. In addition, we combine these in situ observations with RA data for 106 lakes, of which 86 have observations from at least two of the satellites ERS-2, ENVISAT, JASON-1, and JASON-2 for the period 1995–2010, and at least one of the satellites JASON-2, SARAL, JASON-3, Sentinel-3A, and Sentinel-3B for the period 2013–2022. The lake sample (gauged and RA) spans across Sweden's longitudinal and latitudinal gradient (Figure 1), with varying elevations, surface areas, and average long-term discharge flowing through the lakes (Figure 2).

2.2. Hydroclimatic Data Sets and Lakes Characteristics

The physical characteristics of lakes are obtained from the HydroLAKES data set (Messager et al., 2016; www.hydrosheds.org/products/hydrolakes; accessed on 2023/01/06). Due to the shorter distance between satellite ground tracks in higher latitudes, more lakes are covered by RA data in Northern than Southern Sweden (Figures 1 and 2).

To explore the drivers of water level changes, we use daily precipitation and temperature data from in situ hydroclimatic stations operated by the Swedish Meteorological and Hydrological Institute. The data is provided as interpolated 4-km grids and freely available on the web (www.smhi.se/data/ladda-ner-data/griddade-nederbord-och-temperaturdata-pthbv; accessed on 2023/12/13). For each lake, we calculate the average precipitation and temperature in the upstream hydrologic basin of the inlet to each lake. Based on these data, we calculate the average, the trend, and the standard deviation of precipitation ($\bar{P}$, P_T, P_σ, respectively) and temperature ($\bar{T}$, T_T, T_σ, respectively) over the study periods. To delineate the upstream basin, we use the 50-m resolution National Digital Elevation Model (DEM) provided by the Swedish Mapping, Cadastral, and Land Registration (Lantmäteriet) Authority following standard procedures. To enhance our understanding of the directional flow toward the lakes

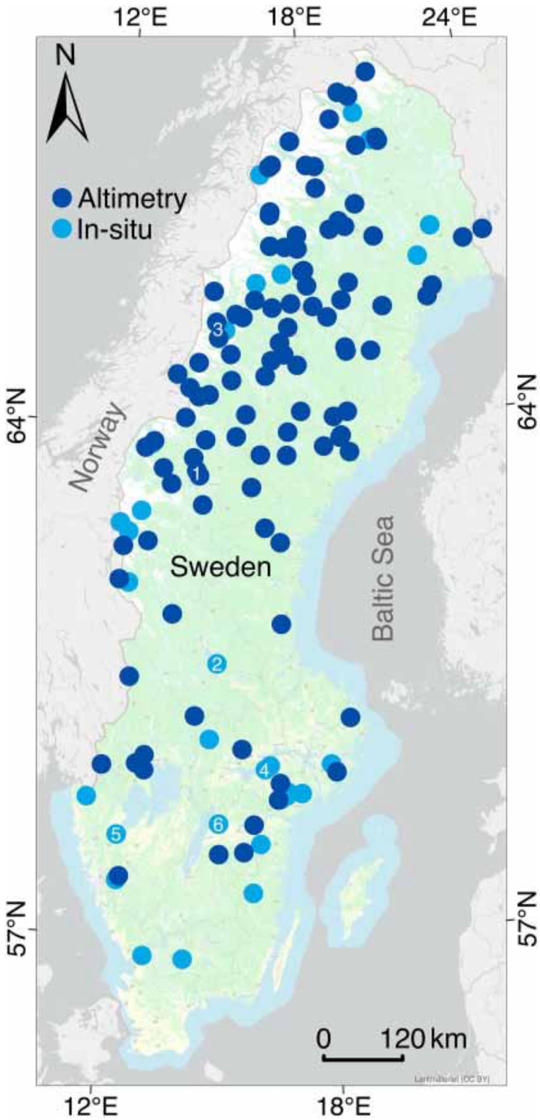

Figure 1. Location of the 38 lakes with daily water level data provided by the Swedish Meteorological and Hydrological Institute (SMHI) and the 106 lakes with potential RA data. The numbers point to six regulated lakes whose hydrographs we show in Figure 11.

and to improve the precision of flow accumulation and pour point locations, we use the Free-flowing Rivers (FFRs) data set, which comprises a comprehensive geometric network of global riverine systems (Grill et al., 2019). Since a lake may not be regulated by regulating structures at its outlet but may receive regulated flows from upstream, the pattern of water levels may be subject to regulatory schemes occurring upstream. We classify the selected lakes into four categories:

1. Non-regulated lakes (N): The lake is not regulated at its outlet, and the inflows into the lake are not regulated upstream (in other lakes or rivers).
2. Lake receiving regulated inflows (U): The lake is not regulated at its outlet, but the inflows into the lake are regulated upstream (in other lakes or rivers).
3. Regulated on site (R): The lake is regulated at its outlet, but the inflows into the lake are not regulated upstream (in other lakes or rivers).
4. Lakes subjected to both local and upstream regulation (U + R): The lake is regulated at its outlet, and some of the inflows into the lake are regulated upstream (in other lakes or rivers).

To perform this classification, we utilize four data sets indicating the geo-locations of dams and hydropower infrastructure; (a) HOLAS II Data set: Hydropower dams-2017 (available at http://vattenwebb.smhi.se/regulations/) provided by The Baltic Marine Environment Protection Commission (Helsinki Commission, HELCOM), SMHI, and hydropower companies, (b) The Global Dam Tracker (GDAT) data set showing the geo-coordinates of 35,000 dams (Zhang & Gu, 2023), (c) GeoDAR: Georeferenced global Dams And Reservoirs data set for bridging attributes and geolocations (Wang et al., 2022), and (d) GOODD data set of more than 38,000 georeferenced global dams (Mulligan et al., 2020; Soesbergen et al., 2020). We run the Wilcoxon rank sum test on all combinations of lake regulation categories to see if the differences between groups in terms of water level trends and variability are statistically significant ($p < 0.05$). A higher p-value obtained from the Wilcoxon test between two data sets indicates a lower probability that the medians of the two distributions are different.

2.3. Background on Satellite Altimetry for Water-Level Estimation

Altimeter sensors transmit a microwave signal toward the Earth's surface and measure its two-way travel time to calculate the distance between the satellite and the water surface, also known as the range (R) directly below the satellite (nadir). For inland waters, the range between the satellite and the water surface obtained using the re-tracking algorithm Ice-1—based on the Offset Center of Gravity (OCOG) algorithm (Bamber, 1994; Wingham et al., 1986)—filters out the signal from non-water surfaces and generally provides better results for water level retrievals than other retracking algorithms (e.g., Frappart et al., 2006; Shu et al., 2021; Sulistioadi et al., 2015). The Level-2 RA products containing re-tracked ranges were used in this study. Correspondingly, the range needs to be adjusted due to necessary corrections related to the travel of the electromagnetic wave through the atmosphere (i.e., ionosphere, dry and wet troposphere; C_{ion}, C_{dry}, and C_{wet}) and geophysical phenomena (i.e., solid Earth tide and geocentric polar tide; $C_{solid\ Earth}$ and C_{pole}). All the corrections are included in the RA data (GDR; Geophysical Data Records) provided by the Center for Topographic Studies of the Ocean and Hydrosphere (CTOH—https://ctoh.legos.obs-mip.fr). Atmospheric corrections are calculated using troposphere electron content and meteorological model outputs over land surfaces. Geophysical corrections are computed by modeling the astronomical forces between celestial bodies such as the Sun and Moon and hydrodynamic time-stepping models (Andersen & Scharroo, 2011). Finally, water level heights are estimated by subtracting the geoid height—h_N in Equation 1 derived from EGM2008 (Pavlis et al., 2012)—and the corrected range from the satellite height (H_s) (Cretaux et al., 2017; Nielsen et al., 2022):

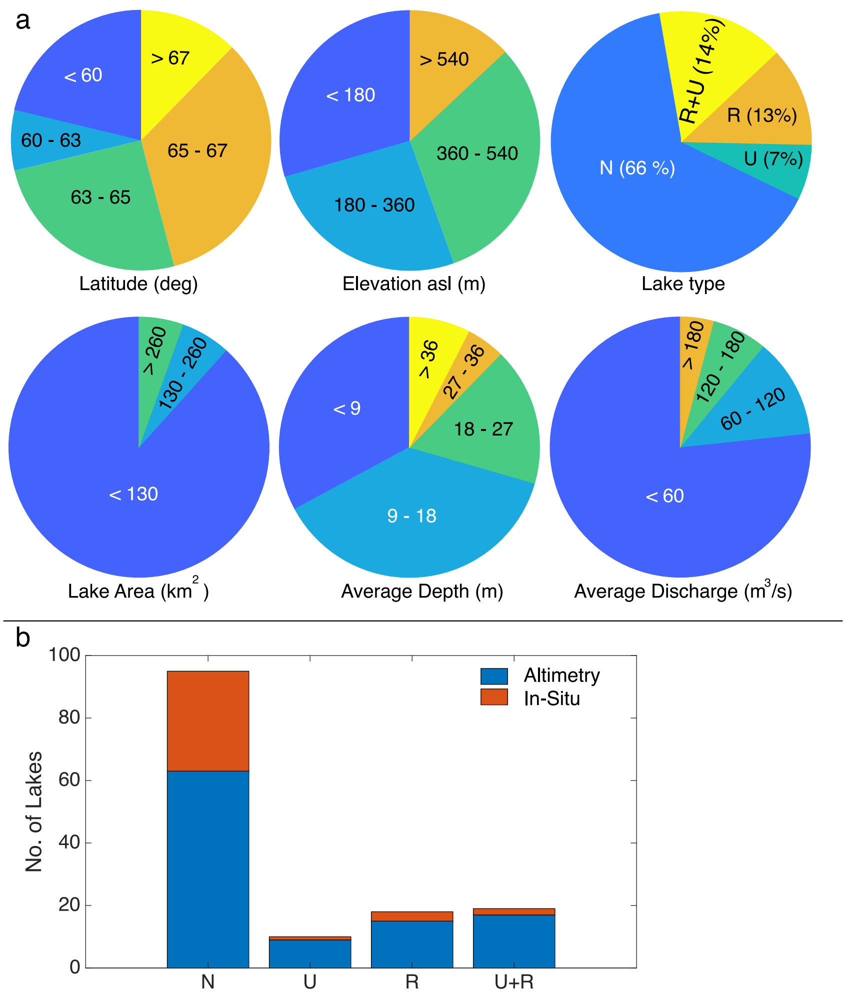

Figure 2. (a) The physical characteristics of the selected lakes, categorized as Non-regulated lakes (N; blue), Upstream-regulated regimes (U; aquamarine), Regulated lakes (R; orange), and with both upstream and direct regulatory structures (U + R; green). Numbers refer to the number of lakes in each category. (b) Number of lakes per regulation category and the origin of the data (in situ or RA).

$$h_A = H_S - (R + C_{\text{ion}} + C_{\text{dry}} + C_{\text{wet}} + C_{\text{solid Earth}} + C_{\text{pole}}) - h_N \tag{1}$$

The altimetry missions cover the period from 1995 to 2022 (Figure 3) and Table S1 in Supporting Information S1 summarizes the characteristics of those missions.

2.4. Time Series of Lake Water Levels

We use the Altimetry Time Series software (AlTiS) developed by CTOH (Frappart, Zeiger, et al., 2021) to process altimetry GDR files and build water-level time series. The graphical interface of AlTiS software displays all the geophysical and atmospheric corrections and ranges from all the re-tracking algorithms present in the GDR files, as well as other waveform-derived parameters such as the backscatter and peakiness, together with the brightness temperatures from the radiometer onboard the satellite through all the cycles of a chosen ground track. It also provides altimeter height with reference to the same geoid model (and the same ellipsoid). First, we mask the data from non-water areas with the lake polygons of the HydroLAKES data sets (Messager et al., 2016). When imported into the AlTiS software, the GDR files may contain unreliable data values not associated with water levels but rather with outliers and non-water surface levels. Consequently, we need an initial approximation of water levels to differentiate the GDR data relevant to water level measurements from the confounding noise. We use the

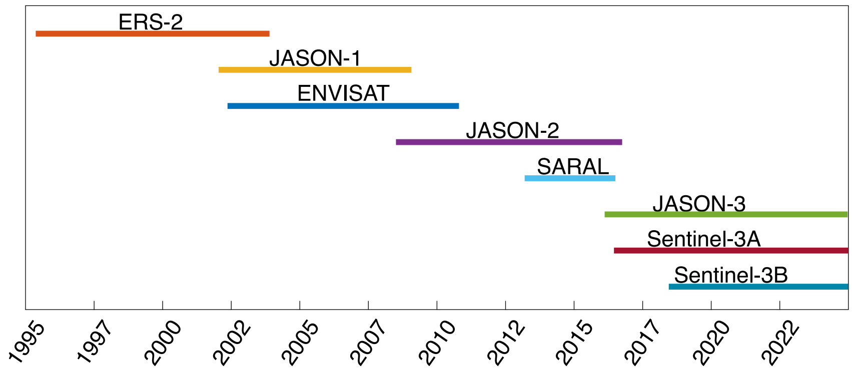

Figure 3. The timeline of altimetry satellites used in this study, with Table S1 in Supporting Information S1 summarizing the characteristics of those missions.

elevation data in the vicinity of the lakes as derived from Google Earth, which is based on Digital Elevation Models such as the Shuttle Radar Topography Mission (SRTM), and subsequently remove the GDR data falling beyond the range of elevation of the ground (i.e., >5 m). Then, we conduct a step-by-step manual cleaning process to eliminate visually discernible outliers within the GDR data values (Figures S1 and S2 in Supporting Information S1). In the final stage, we retain only the RA observations falling within the range of "median ± standard deviation" for each pass or temporal instance. We exclude water level data obtained during the winter months, as most lakes in Sweden experience freezing conditions, and altimetry estimations over frozen surfaces are inaccurate (Nielsen et al., 2020; Ziyad et al., 2020). Subsequently, we calculate the median of these observations (for each altimetry pass) to obtain the water level on the respective dates. This procedure is re-iterated for every altimetry satellite track, yielding the complete water level time series.

It is worth mentioning that there is a general systematic discrepancy among water level measurements derived from different satellites due to factors such as the different orbits of each sensor, correction models, and reference datums used (Li et al., 2019; F. Xu et al., 2022). One common practice to identify such a shift is calculating the difference between the mean water levels obtained from two sensors with overlapping observation periods (Li et al., 2019; F. Xu et al., 2022). However, in our data set and for 1995–2022, the overlap only exists for 22 lakes with JASON-2 data between 2010 (i.e., end of the ENVISAT mission) and 2013 (i.e., beginning of the SARAL mission). Figure 3 shows the timeline of satellites and how JASON-2 covers the gap between the two shorter periods, 1995–2010 and 2013–2022. Note that all altimeter heights are provided with reference to the same geoid model (EGM2008) or the same ellipsoid—WGS84; see Salameh et al. (2018) for the correction applied to reference the data on the same ellipsoid using AlTiS. The quality of RA estimations for each lake is calculated as the mean of the standard deviations on each date (WL_Q) corresponding to each satellite pass. Moreover, the accuracy of RA measurements is assessed by comparing RA water levels with in situ measurements in two large lakes with both long-term gauged observations and RA data (Lake Hjälmaren and Lake Vättern).

2.5. Water Level Trends and Variability

Based on the availability of the altimetry missions and considering the periods of overlap, we perform our analysis across two different periods:

1. The long period 1995–2022, with water level data from JASON-2 and at least one of the satellites ERS2, ENVISAT, or JASON-1, and at least one of the satellites SARAL, JASON-3, Sentinel-3A, and Sentinel-3B (22 lakes). In this case, we considered water levels from Sentinel-3A as the baseline. We calculated the shift as the difference between its mean water level and that computed from the other satellites in the overlapping period.
2. The recent short period 2013–2022, with water level data from at least one of the satellites SARAL, JASON-3, Sentinel-3A, and Sentinel-3B (all 106 lakes). Here, similar to case 1, we considered water levels from Sentinel-3A as the baseline and calculated the shift as the difference between its average water level and that computed from the other satellites in the overlap period.

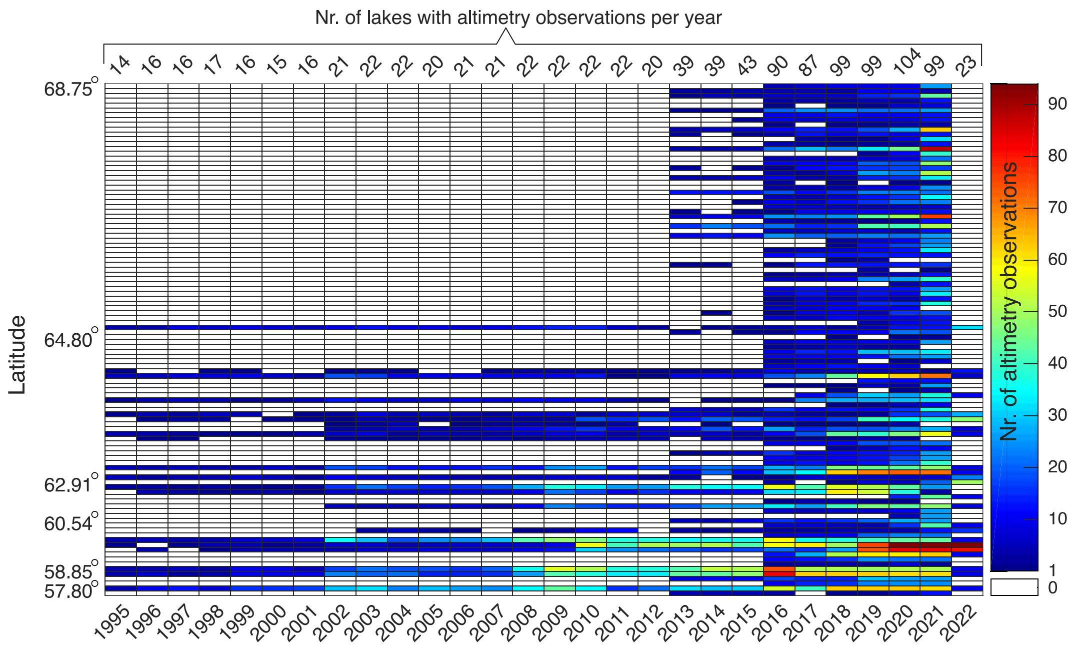

Figure 4. The number of RA observations available during each year and in each lake (see color gradient). The vertical axis shows latitudes ordered from lower to higher latitudes; the numbers on the top horizontal axis are the total number of lakes with RA observations each year.

The data availability is not uniform across the lakes. In the first 3 years of the shorter period (i.e., 2013–2015), 40% of the lakes have RA data (around 40 out of 106), but when combined with in situ gauged observations, the number of lakes with data availability increases to more than 50% of all lakes. Moreover, 91% of the lakes have RA data availability between 2016 and 2021, which increases to 93% when adding in situ observations (Figure 4).

To measure the range of variation of water levels in a specific lake during the observation period, we estimate the mean annual Dynamic Storage (DS; the average of yearly maximum minus yearly minimum) and the annual DS trend (DS_{AT}) with the Theil-Sen trend estimator. We also calculate each lake's annual, spring, summer, and autumn water level trends (WL_T, $WL_{SP\text{-}T}$, $WL_{SM\text{-}T}$, and $WL_{AU\text{-}T}$, respectively). 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). The Theil-Sen trend is more robust and less sensitive to outliers than standard regression methods such as the ordinary least squares (Mailhot et al., 2019). We calculate the statistical significance of the trends (p-value) by a non-parametric two-sided Wilcoxon signed rank test on all estimated pairwise slopes (Saplıoğlu & Güçlü, 2022). The null hypothesis is that no significant trend exists between the pairwise slopes at the 5% significance level; consequently, rejecting the null hypothesis ($h = 1$) implies that the pairwise slopes have a non-zero median and the time series has a trend.

To differentiate the influence of human activities (e.g., regulation), climate, and lake physical characteristics on water level changes and trends across the sample of lakes, we compute a correlation matrix based on Pearson's correlation, including mean annual DS and WL_T, precipitation and temperature averages ($\overline{P}$ and $\overline{T}$), variability (P_σ and T_σ) and trends (P_T and T_T). We construct two matrices, one for regulated lakes (U, R, U + R) and one for unregulated lakes (N).

3. Results and Analyses

3.1. Quality and Validation

The quality of RA-derived water levels is evidenced by the low mean of the individual standard deviations of every cycle from RA in most lakes from 1995 to 2022 (Figure 5a, mode = 0.04 m). Lake Alsensjön in the middle and Lake Norra Nordsjö in the northeast of the country (as shown by arrows), with surface areas of approximately 40 and 8.0 km^2, respectively, exhibit the largest standard deviations (i.e., ~0.07 m). The lower quality of the older

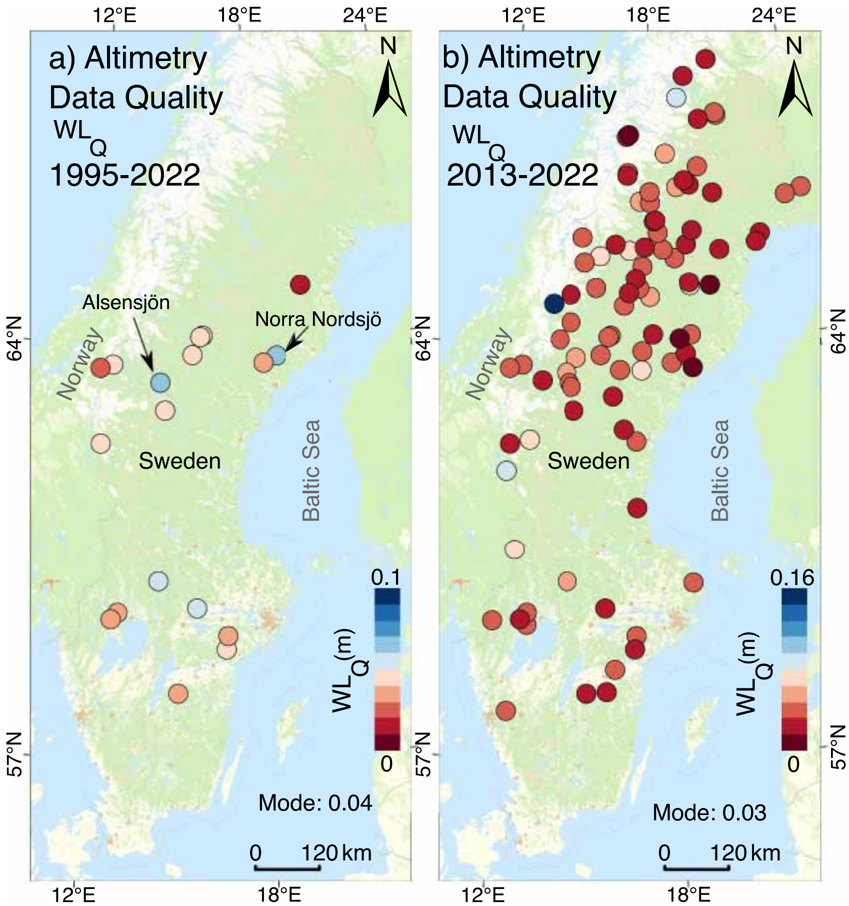

Figure 5. The quality of the RA measurements (WL_Q) during the period (a) 1995–2022 and (b) 2013–2022. Mode is the average of the most frequent bin for the histogram of all lakes.

sensors is evident in the time series of water levels, where ERS-2 and JASON-1 sensors show high standard deviations in Lake Hjälmaren and Lake Vättern, two of the largest lakes in Sweden (Figure 6). In addition, the quality is lower in lakes in the northern mountainous regions of Sweden, especially in mountainous lakes near the Norwegian border (Figure 5b).

Taking the example of the largest lakes in Sweden, Lake Hjälmaren and Lake Vättern, to study the accuracy of altimetric measurements, we find that the water levels derived from older sensors (e.g., ERS-2 and JASON-1) are generally less accurate than the new ones (Figure 6 and Table 1). On the other hand, Sentinel-3A and Sentinel-3B satellites exhibit the highest accuracy among the other altimetry satellites, with Root Mean Square Errors (RMSE) of 11 and 5 cm (in Lake Hjälmaren and Lake Vättern, respectively; Table 1). During 1995–2022, the difference between in situ- and RA-derived water level trends is 0.11 cm/yr in Lake Hjälmaren and 0.03 cm/yr in Lake Vättern (Table 2). During the shorter period 2013–2022, these differences increase to 0.7 cm/yr in Lake Hjälmaren and 1.7 cm/yr in Lake Vättern (Table 2). Regarding DS, the differences between in situ- and RA-derived DS during 1995–2022 are 17 cm in Lake Hjälmaren for a mean DS of 37 ± 9 cm (24%) and 6 cm in Lake Vättern for a mean DS of 26 ± 7 cm (30%), which decrease to 1 cm during the shorter period 2013–2022 for both lakes (Table 2).

3.2. Lake Water Level Changes and Trends

Regarding water level variability, the highest mean DS (representing the total seasonal change within the year) in 1995–2022 is found in northern Sweden (~2.2 m), with the most frequent value being around 0.59 m (Figure 7a and Figure S3 in Supporting Information S1). It is worth noting that the annual DS has been mostly decreasing by 3.8 cm/yr overall (Figure 7b). Regarding long-term water level changes, 52% of lakes show an increasing trend

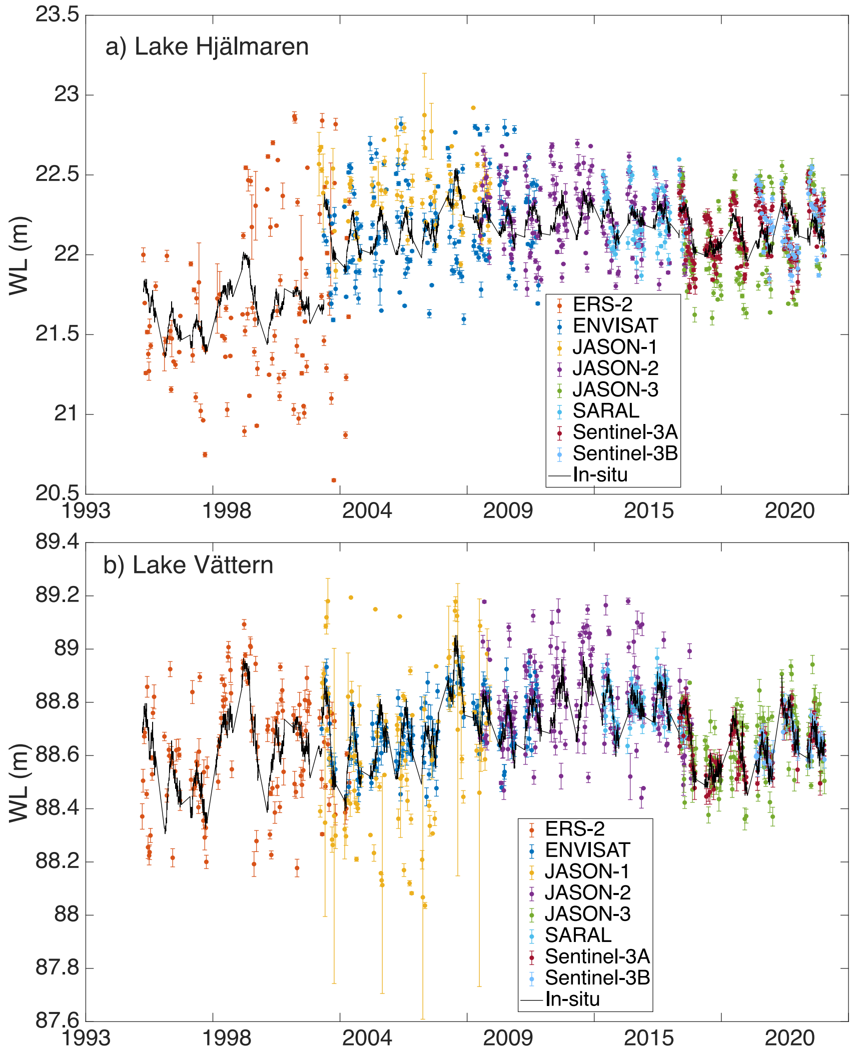

Figure 6. Water levels with reference to the WGS85 ellipsoid derived from different altimetry sensors and in situ measurements for two regulated lakes: (a) Lake Hjälmaren and (b) Lake Vättern.

Table 1
Accuracy of the RA Measurements Explained by the Root Mean Square Error (RMSE) of Altimetry Sensors for Water Level Estimation When Compared With In Situ Data in Lake Hjälmaren and Lake Vättern

	RMSE (cm)	
Satellite	Hjälmaren	Vättern
ERS-2	55	22
JASON-1	24	28
ENVISAT	28	8
JASON-2	19	18
SARAL	14	6
JASON-3	19	13
Sentinel-3A	11	5
Sentinel-3B	11	4

and 43% a decreasing one (Wilcoxon, $p < 0.05$, large circles; Figure 7c). Most increasing trends occur in northern Sweden, and most decreasing trends occur in the south (Figure 7c; see regional patterns shown by the two ellipses). Interestingly, the lakes with higher mean annual DS (Figure 7a) also show higher annual DS trends and water level trends (DS_{AT} and WL_T indicated by arrows in Figure 7b and 7c).

Regarding the seasonal water level trends of spring, summer, and autumn ($WL_{SP\text{-}T}$, $WL_{SM\text{-}T}$, and $WL_{AU\text{-}T}$, respectively), these are generally 3–4 times higher than the overall annual trends (Figures 7d–7f). Increasing spring trends in mountainous areas in the north may be attributed to the recent earlier snowmelt (Figure 7d). Water levels generally decrease across all seasons in the south and only during summer in the north. In the north, water levels increase during spring and autumn (Figure 7e). The decreasing water levels in the north can be potentially explained by increasing evaporation from increasing temperatures in all summer months (June, July, and August) and decreasing precipitation in June and July (Figure S5 in Supporting Information S1).

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Table 2

Water Level Trends and DS for Lake Hjälmaren and Lake Vättern as Obtained From In Situ and RA Data During 1995–2022 and 2013–2022

	Hjälmaren		Vättern	
	In situ/RA		In situ/RA	
Period	Trend (cm/yr)	DS (cm)	Trend (cm/yr)	DS (cm)
1995–2022	−0.29/−0.18	37/54	−0.07/−0.10	26/32
2013–2022	−0.7/0	41/40	−3.1/−1.4	25/26

A similar analysis in the shorter period 2013–2022 improves the spatial and temporal resolution of changes in water levels and enables the recognition of spatial patterns of change throughout the country (Figure 8). Although the spatial distribution of the mean annual DS resembles that of the longer period (Figure 8a), its trends in the shorter period are larger, with the mode being in the opposite direction (increasing; Figure 8b). Moreover, although the overall and seasonal trends of water levels are noticeably larger within the more recent short period (Figures 8c–8f), the distribution of increasing and decreasing trends resembles that of the longer period. Finally, it is worth noting that during spring (the melting season), there are many lakes in the north exhibiting increasing trends (Figure 8d), while during summer, water

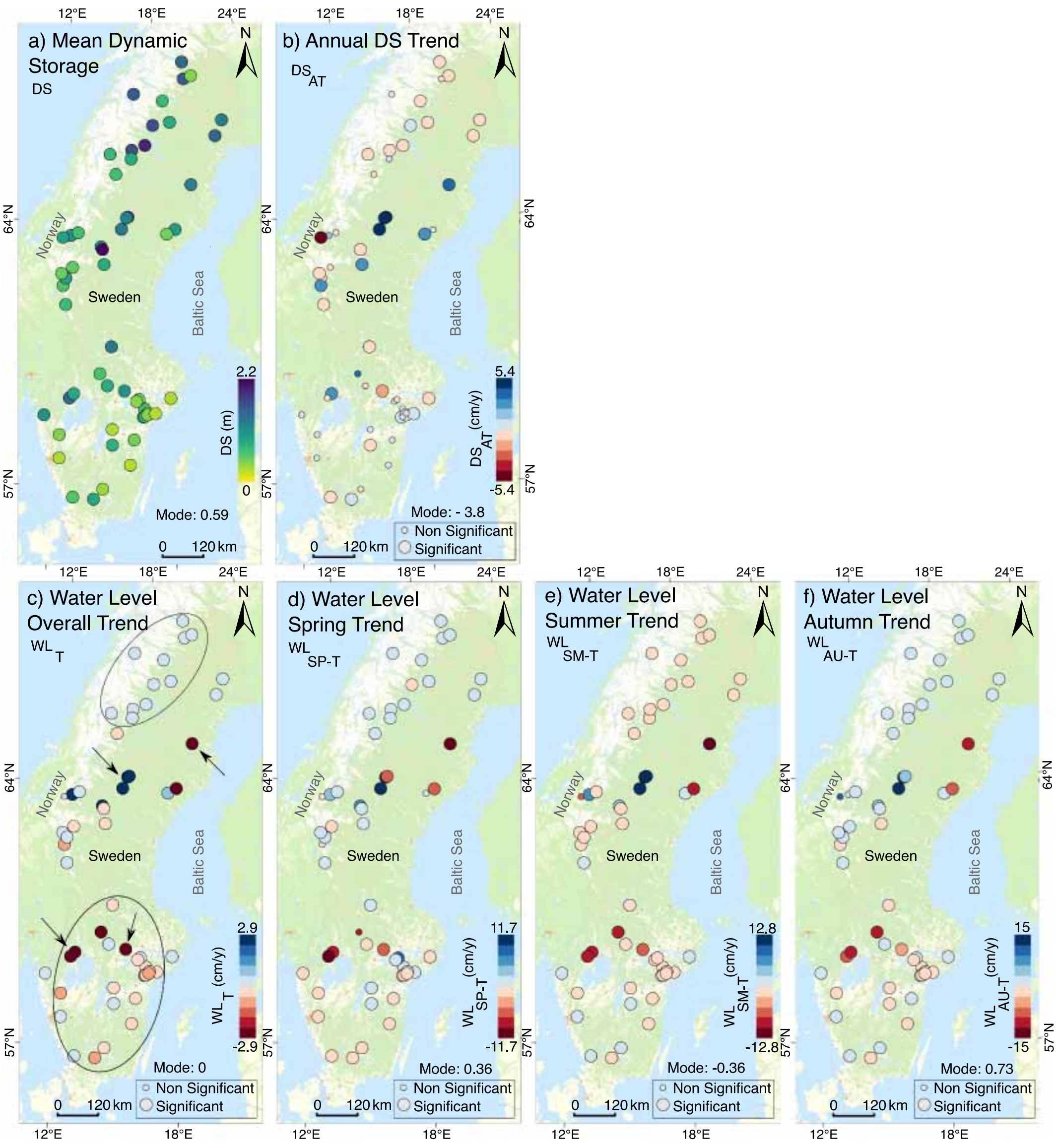

Figure 7. Water level statistics within the period 1995–2022 (a) the variability of water levels based on the mean annual Dynamic Storage (DS), (b) the annual trend of DS, (c)–(f) the annual, spring, summer, and autumn trends of water levels (WL_T, WL_{SP-T}, WL_{SM-T}, WL_{AU-T}) in lakes from both RA and gauges. For the case of the trends, big circles show a significant trend; Wilcoxon test p-value < 0.05, with a blue shade showing a positive trend and a red a negative one. Arrows show the highest values, and ellipses show regions with consistent increasing and decreasing trends. The mode is the average of the most frequent bin for the histogram of all lakes.

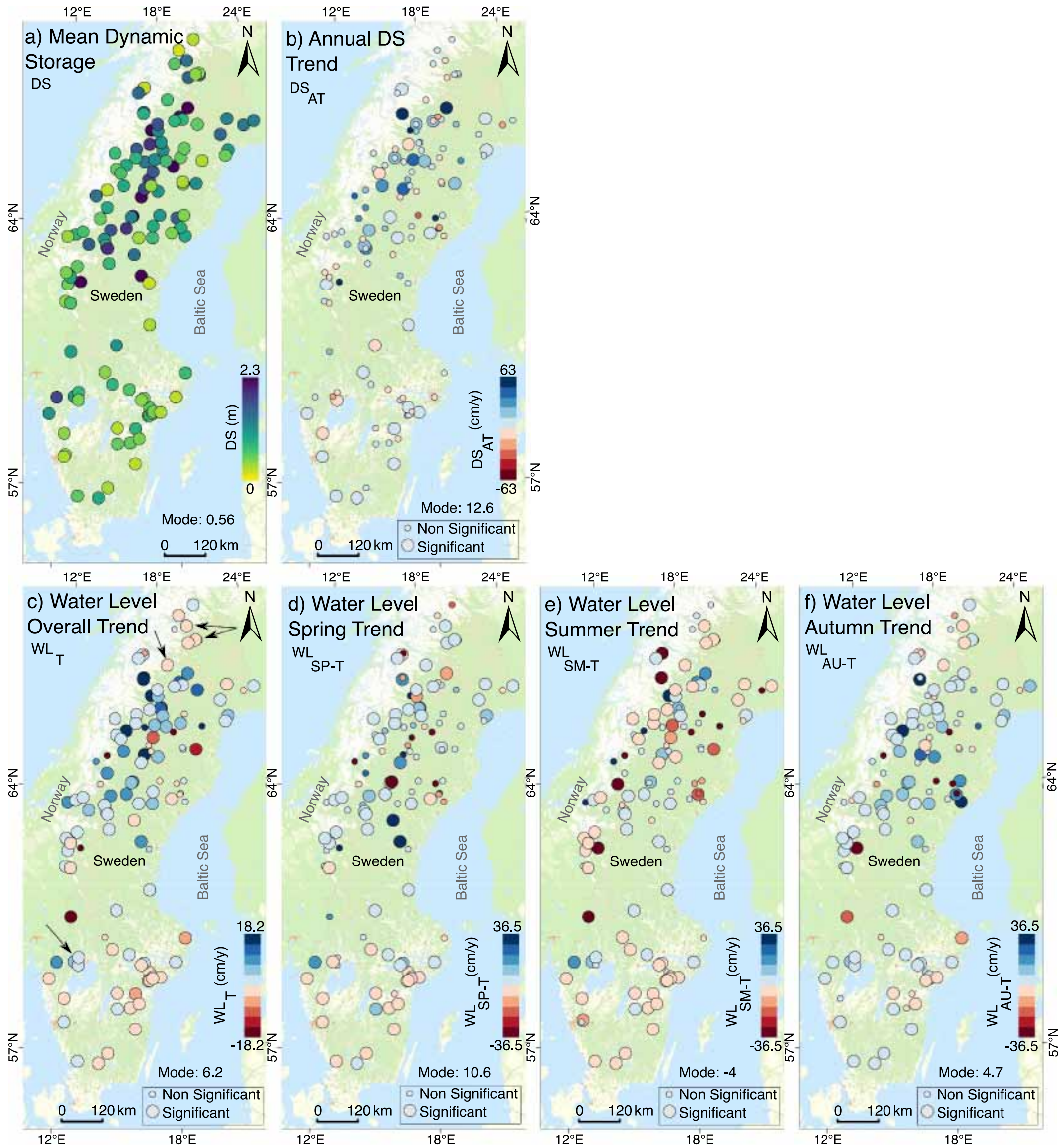

Figure 8. Water level statistics within the period 2013–2022 (a) the variability of water levels based on the mean annual Dynamic Storage (DS), (b) the annual trend of DS, (c)–(f) the annual, spring, summer, and autumn trends of water levels (WL_T, $WL_{SP\text{-}T}$, $WL_{SM\text{-}T}$, $WL_{AU\text{-}T}$) in lakes from both RA and gauges. See Figure 7 for details.

levels mostly exhibit a decreasing trend (Figure 8e), followed by an increasing trend in the autumn (usually with higher precipitation; Figure 8f). The increased water levels in spring in northern lakes relate to the fact that many of the lakes in the north are located in the mountains (high altitudes) and get more snowfall in the winter. In northern Sweden, 50% of the annual precipitation falls as snow, and the annual runoff is dominated by snowmelt (Hellgren & Bartsch, 2023). In the north, snow is deeper and lasts longer in these high-altitude areas, whereas in the south, snow cover is present in less than 50% of the winter (and accounts for only 10%–20% of precipitation).

3.3. Potential Drivers of Water Level Changes

We also explored how the interannual variability of water levels (i.e., DS) or their trends could be explained by the regulation of the lake or its upstream hydrological basin. We found that non-regulated lakes (N) had the smallest trends in water level and mean DS (Figures 9a and 9b). In general, non-regulated lakes show smaller DS than lakes affected by any regulation (R, U, U + R), which evidences a clear effect of regulation on DS ($p < 0.05$; Wilcoxon rank sum test, Table 3). On the contrary, the highest p-value is observed between the water level trend

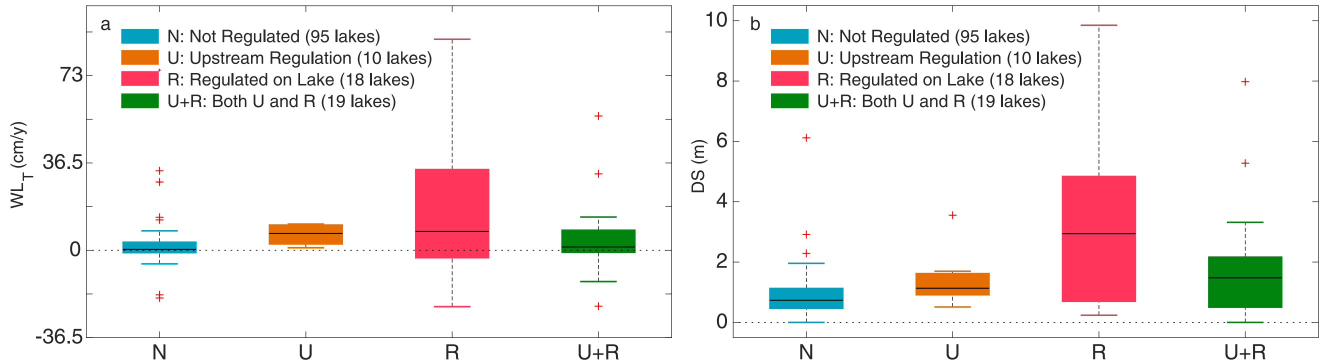

Figure 9. Distributions of (a) trend and (b) mean annual Dynamic Storage (DS) during the period 2013–2022 for the four categories of lake types: Non-regulated lakes (N), Upstream regulatory regimes (U), Regulated lakes (R), and lakes subjected to both upstream and direct regulatory structures (U + R).

(WL_T) of the lakes regulated on-site and those upstream (p-value = 0.83; Table 3), implying that these are not different, at least based on the current sample of lakes.

Regarding the climatic forcing on change in water levels from changes in precipitation and temperature, the Pearson's correlation matrix for regulated lakes (i.e., R, U, U + R) reveals a low but statistically significant correlation (p-value < 0.05) between water level variability (i.e., DS) and mean precipitation ($\bar{P}$), its trend (P_T) and variability (P_σ) (Figure 10b). This climatic forcing is more evident in regulated lakes than in non-regulated ones. On the other hand, the observed correlation between DS and lake elevation may be attributed to the differences between the hydrological regimes in northern Sweden (which are in the mountains) and the south, where lowland lakes are most common.

A hydrograph based on water levels for specific regulated and unregulated lakes in both north and south Sweden elucidates the effects of regulation on the hydrologic regimes of lakes (Figure 11). The difference in these regimes is exemplified by taking some lake examples with in situ measurements (as they have the highest data availability). Among these examples shown in Figure 11, six lakes are regulated (three in the northern, three in the south), and six are unregulated, with pairs of regulated and unregulated lakes in similar locations. Five of the regulated lakes shown in Figure 11, are the largest lakes in Sweden. In all selected lakes in northern Sweden, the water level increases during the spring and peaks in the summer. Since this increase occurs with low precipitation during spring, we can assume that such an increase in water levels is mostly due to snowmelt (see Figure 11a, P in April and May). However, after summer, water levels decrease along with precipitation. The decrease is milder in the regulated lakes than in unregulated lakes.

In the south, summer has the highest water levels in regulated lakes and the lowest in unregulated lakes (Figure 11b). In unregulated lakes, the pattern of water level considerably changes from that observed in the north.

Table 3
The p-Values of the Wilcoxon Rank Sum Test Between Pairs of 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 (U + R)

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

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

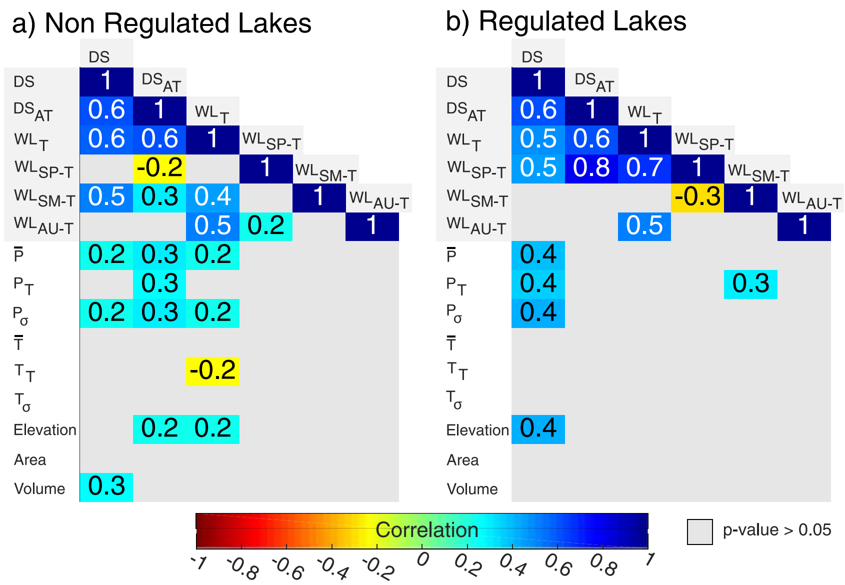

Figure 10. Pearson's correlation matrix in (a) Non-Regulated lakes (N; Figure 9) and (b) Regulated lakes (U, R, and U + R; Figure 9) between water level trends and variabilities (see Figure 7), precipitation (average $\overline{P}$, trend P_T, and standard deviation P_σ), and temperature (average $\overline{T}$, trend T_T, standard deviation T_σ) 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 < 0.05).

A decrease in water levels occurs in late spring despite increasing precipitation, probably as the effect of snowmelt on water levels is shorter and occurs early in spring. Then, the low water levels in summer may be due to high evaporation in late spring as temperature increases. After summer, water levels increase once again with increasing precipitation and decreasing temperatures. Regarding the regulated lakes, in comparison to the north, the peak in water level shifts from late spring to summer and is followed by a decrease during autumn (more pronounced than in the north).

The dominant regulatory structure of surface water in Sweden is dams (90%), especially for hydropower and mining. The remaining 10% of regulatory structures include dikes, levees, and canals mainly located in the south and used for inland transportation between lakes (e.g., Hjälmare Canal connecting the two large lakes in the south, Mälaren and Hjälmaren), flood control, drinking water, and agriculture (Hellgren & Bartsch, 2023). The dams for irrigation are located in the south (Hellgren & Bartsch, 2023). Hence, the purpose of regulation in the south may also partly explain other differences in the seasonal water level patterns between regulated lakes. The regulatory scheme of the lakes in Figure 11 is multi-purpose and all of them have hydropower. Lake Fattjaure in Figure 11 (number 3) has only an upstream regulatory regime (U) that can explain the similarity of the water level hydrograph of this lake with unregulated lakes.

4. Discussion

We showed that water levels in the north of Sweden are increasing while most southern lakes have decreasing trends. The increasing trends in water levels in autumn can be related to recent increases in autumn runoff. For instance, these increments are about 3% per decade over the past 100 years, as modeled by Arheimer and Lindström (2015) (also see Figure S5 in Supporting Information S1). Furthermore, the increasing lake water level trends in spring may be attributed to the early spring snowmelt coinciding with increasing spring temperatures (Arheimer & Lindström, 2015; Hellgren & Bartsch, 2023). Finally, the decreasing overall and summer water level trends in southern Sweden can be potentially explained by the low precipitation of the recent dry summers and steadily increased temperature rates leading to increased evaporation rates (Figure S5 in Supporting Information S1).

Many studies have focused on identifying the drivers of changes in water resources; however, answering the question of which driver plays a more important role is not straightforward (Chao et al., 2008; Dong et al., 2022;

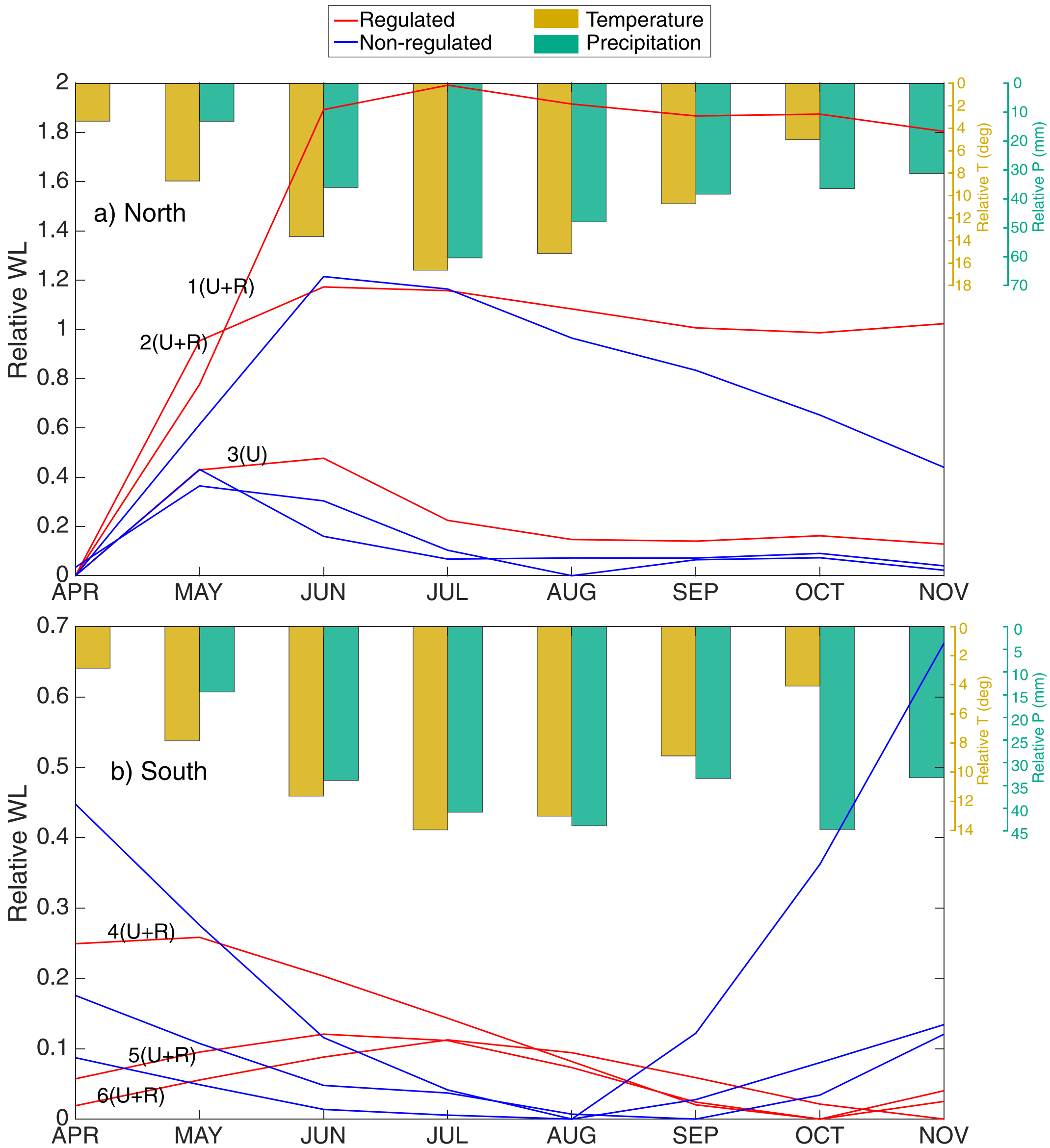

Figure 11. Mean monthly water level in six Regulated and six Non-regulated lakes during 1995–2022 (a) in the south and (b) in the north. To ensure consistent scales for all lakes, we subtracted the lowest monthly water level mean from each month, resulting in the Relative WL. Similarly, the bars show relative temperature (yellow) and precipitation (green) during 1995–2022. The numbers on the red solid lines refer to the names of the regulated lakes shown also in Figure 1; 1:Storsjön, 2: Siljan, 3:Fattjaure, 4:Hjälmaren, 5:Vännern, and 6:Vättern. U means upstream regulated, R means directly regulated, and U + R means both types of regulation. All the regulatory structures are multi-purpose including hydropower.

Gudmundsson et al., 2021; Jaramillo & Destouni, 2015). For instance, Destouni et al. (2013) showed that regulated basins in Sweden experienced an increase in relative evapotranspiration not found in unregulated basins. Although the study by Destouni et al. (2013) focused on evapotranspiration and runoff change in Swedish basins to determine the effects of regulation, these hydrological fluxes can, at some point, also be related to lake water levels.

Additionally, a study by Arheimer et al. (2017) showed that the primary contributor to flow regime change in snow-fed rivers in Sweden during the 21st century would be hydropower regulation; however, they also found that temperature increases may also partly explain a decrease in river runoff variability. This is aligned with our findings showing that the mean annual DS in Sweden has been mostly decreasing since 1995 ($DS_{AT} = -3.8$ cm/yr). Regarding the effects of regulation, the influence of water regulation schemes on water resources is not only bound to snow-dominated areas but also evident in other world regions (e.g., Botter et al., 2010; Jaramillo & Destouni, 2015; Sun et al., 2021; Zamora et al., 2020). For instance, Xie et al. (2022) showed that while human activities and climatic variability affect terrestrial water storage in the Yellow River basin in China, reservoir operation plays a more important role in terrestrial water storage changes than climate variability.

Finally, it is worth noting that our results also agree with global findings regarding lake water level changes. For example, Cooley et al. (2021) studied lake water levels using laser altimetry to find that human-managed reservoirs are responsible for 57% of the global surface water storage variability and in the northern high latitudes, up to 50%. In addition, a recent study by Yao et al. (2023) found storage declines in 53% of a sample of lakes worldwide, attributed to water consumption and global warming.

Regarding the quality of RA observations, large mean, standard deviations are more likely to occur in smaller lakes with the shortest along-track width or in the presence of topography and vegetation, as mentioned in previous studies (e.g., Baup et al., 2014; Sulistioadi et al., 2015). The quality of RA water level data is higher in the shorter period 2013–2022 (Figure 5b), probably because older sensors used during the longer period are less precise after data cleaning than the more recent ones in good agreement with previous results (e.g., Bogning et al., 2018; Frappart, Zeiger, et al., 2021; Normandin et al., 2018; Shu et al., 2021).

So, can satellite altimetry alone provide a comprehensive understanding of water level changes and their main drivers for Swedish lakes? We showed here that the altimetry data quality calculated as the average of altimetry standard deviations for each lake is small. The accuracy for the two selected lakes is high, and previous studies have demonstrated the reliability of altimetry observations for inland waters by validating them with in situ measurements (Crétaux et al., 2015; Frappart, Blarel, et al., 2021; Kraemer et al., 2020). However, our findings showed that there might be slight differences between water level trends derived from altimetry and those obtained from in situ measurements due to the generally lower temporal resolution of altimetry data. Although using multiple altimetry satellite data can enhance the temporal resolution and coverage of altimetry observations in lakes, careful attention is needed when considering the global-scale analysis of lake water level trends and variability solely reliant on satellite altimetry data (e.g., Cooley et al., 2021; N. Xu et al., 2022). Hence, combining laser altimetry data to densify the number of observed waterbodies might not be sufficient. For example, Cooley et al. (2021) and N. Xu et al. (2022) quantified global changes in lake water levels observed by the ICESat-2 laser altimetry satellite (by NASA) and a combination of ICESat and ICESat-2 and found that the density of their altimetry observations was as low as two to four observations in 22 months. This can skew the interpretation of water level variability.

Regarding the parameters we used to study any link between climate variability and water levels, we did not consider background climate variations (e.g., El Niño). However, a study by Kraemer et al. (2020) on water level trends in 200 lakes worldwide between 1992 and 2019 showed that background climate variations could partly explain the long-term trends of lake water levels derived from satellite altimetry. The study found that after removing background climate variations from lake water level trends, these trends were smaller but statistically more significant than those before removing background climate variations. In northern Europe, the Arctic Oscillation may hide long-term trends in lake water levels (Kraemer et al., 2020). Therefore, by removing the Arctic Oscillation, we may better quantify the contribution of changes in precipitation and temperature to Swedish lake water level changes.

Finally, it is worth mentioning that we found that only around 700 Swedish lakes fall under the orbit of at least one altimeter, meaning that we can only monitor water levels in at most ∼0.7% of lakes in Sweden. However, data from the newly launched mission Surface Water and Ocean Topography (SWOT) and other future altimetry missions may hopefully increase this estimate. The SWOT is a joint mission developed by the National Aeronautics and Space Administration (NASA) and the French Space Agency (CNES) in partnership with the Canadian Space Agency (CSA) and the UK Space Agency (UKSA). It can provide more than four observations per 21-day repeat cycle in high latitudes, improving our understanding of water level variations (Crétaux et al., 2015; Yoon et al., 2016) and allowing us to compute water storage.

5. Conclusions

We estimated water level trends and variability in 144 lakes in Sweden using satellite altimetry data and in situ measurements. We observed that:

1. The variability of lake water levels, calculated as the mean annual dynamic storage, can reach more than 2 m in some lakes. Overall, dynamic storage appears to be decreasing in a large majority of the lakes during the long period 1995–2022 and mostly increasing in the shorter period 2013–2022.
2. From 1995 to 2022, around 52% of the 144 lakes exhibited an increasing trend in water levels, and 43% a decreasing trend. Most lakes exhibiting an increasing trend were in the north of Sweden, while most lakes showing a decreasing trend were in the south.
3. The decreasing water levels in the north can be potentially explained by increasing temperatures in all summer months (June, July, and August) and decreasing precipitation in June and July. However, there is no strong correlation between water level and precipitation/temperature trends across the groups of lakes.
4. Regarding the potential effects of regulation, we found that the group of unregulated lakes had smaller trends in water level and DS than the regulated groups of lakes.
5. The seasonal pattern of change in water levels in the lakes in the north of Sweden is generally similar between regulated and unregulated lakes, increasing in spring and peaking in summer, after which water levels decrease. Instead, in the south, the seasonal patterns of water levels differ substantially, with spring and summer experiencing water level peaks in regulated lakes and summer experiencing the lowest in non-regulated lakes.
6. Based on selected examples of regulated lakes, we find that the water level regimes of regulated lakes are similar in the north and the south. The regulated lakes in the south show a peak in water level that is more shifted toward summer than that in the north and is followed by a decrease during autumn.

These results highlight the need to continuously monitor Swedish lake water levels and consider lake regulation in water management practices and climate change adaptation policies.

Data Availability Statement

The v2.2.6-0-gf40f10e version number of the AlTiS software was used to obtain lake water levels from GDR altimetry files. The software was developed by CTOH and is freely available at https://gitlab.com/ctoh/altis. Altimetry GDR data used in the study are provided by the CTOH and can be downloaded at https://doi.org/10.17043/aminjafari-2023-altimetry-1. They come from the GDR made available by the space agencies except for ERS-2 which comes from the land and ice sheets retracking performed by CTOH (Frappart et al., 2016).

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