

Evaluation of SWOT HR PIXC version D water level time series of small lakes

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Abstract. ~~Satellite altimetry has successfully monitored inland waters for more than 30 years and is increasingly important as the demand for freshwater grows and climate change accelerates. Launched in December 2022, the~~ The Surface Water and Ocean Topography (SWOT) satellite ~~is the first to provide~~ mission introduces unprecedented 2D spatially distributed elevation measurements, with a 21-day revisit time and better coverage depending on latitude and a nominal requirement to detect lakes as small as 0.06km². ~~radar interferometry to inland hydrology, aiming to evaluate water bodies down to 0.0625 km². Here, we evaluate the~~ Standard operational products, such as LakeSP, are designed for global applicability but may exhibit suboptimal design choices for particular hydrological regimes. To address this, a customized processing workflow utilizing low-level SWOT L2 HR PIXC version D data product (if available at the time of writing) to construct time series of water surface elevation (WSE) and capture their relative WSE change in vD data was evaluated using 37 Danish lakes with a surface area between small Danish lakes (0.25 to 40 km² and 40km² via the summary measures RMSE and Pearson's r) against daily in-situ gauge data from July 2023 to May 2026. The workflow achieves a median root-mean-square error (RMSE) of 5.57 cm and a Pearson correlation coefficient (PCC) of 0.91. We tested six selection criteria to aggregate one WSE value per lake and timestamp. The median unbiased RMSE of SWOT vs gauge is 5.34cm, and the median PCC is 0.91. We of 0.91, similar to LakeSP. Crucially, this approach retains a median of 125 valid timestamps per lake compared to 60 timestamps preserved by the filtered LakeSP product, effectively doubling the temporal resolution and enabling the capture of higher-frequency hydrological variations. Additionally, we find indications that SWOT's PIXC data contains time-varying residual roll-errors over Danish lakes. We demonstrate that our approach performs slightly better than filtered SWOT L2 HR LakeSP prior data from Hydrocron in terms of RMSE and PCC (6.05cm and 0.89), while retaining roughly double the number of valid timestamps over the overlapping period that affect ca 18% of all passes with more than 10 observed lakes covering Denmark.

1 Introduction

Continental water resources are affected by climate and, therefore, are important markers of climate change. In addition, human activities continue to impact rivers and lakes, potentially devastating biodiversity and human existence (Best, 2019). Therefore, it is detrimental-crucial to continuously monitor the relative change in water surface elevation (WSE) of lakes and reservoirs worldwide to understand the underlying dynamics.

25 Traditionally, WSE is precisely measured by in-situ gauges, which can be expensive to install and maintain, and their data may not be public. In addition, the gauges are not evenly distributed across the Earth. Many lakes and rivers in remote areas and economically poor countries remain unobserved (Biancamaria et al., 2016). During the past 30 years, satellite altimetry has become an important, low-cost, freely available supplement in WSE monitoring (Abdalla et al., 2021). Globally distributed WSE time series are available from: Copernicus Land Monitoring Service (Copernicus, 2024), Hydroweb (Crétaux et al., 2011),
30 "Database for Hydrological Time Series of Inland Waters (DAHITI)" (Schwatke et al., 2015), "USDA Lake ~~database~~[Database](#)" (Birkett et al., 2011), and "ESA CCI Lake ECV" (Carrea et al., 2024; ESA, 2024).

The launch of the Surface Water and Ocean Topography (SWOT) satellite mission in December 2022, led by the Centre National d'Études Spatiales (CNES) and National Aeronautics and Space Administration (NASA), represents a new era in satellite altimetry (Fu et al., 2024). It carries a dual-sided cross-track Ka-band Radar Interferometer (KaRIn) (JPL, 2024b), operating
35 at 35.75GHz (Biancamaria et al., 2016), with near nadir incidence angles ~~(?)~~[\(Fjørtoft et al., 2014\)](#). The KaRIn instrument enables SWOT to sense WSE within two ~~50km~~[50 km](#) wide swaths left and right of the satellite, separated by a ~~20km~~[20 km](#) wide nadir gap (Biancamaria et al., 2016; JPL, 2024b). The highest available resolution data product, the High Rate (HR) PIXel Cloud (PIXC), retains measurements outside the defined swaths (JPL, 2023b). This makes SWOT the first altimetry satellite to observe 2D *images* of WSE. SWOT [fundamentally transforms surface water hydrology by providing dense spatial sampling](#)
40 [and temporally coherent observations of water surface slopes \(WSS\)](#). SWOT operates in a 21-day repeat science orbit (cycle) (JPL, 2024b) with an average global revisit time of 11 days (JPL, 2024a). The majority of all lakes are located above 50°N (Lehner and Döll, 2004) which on average, will have at least 2-3 [SWOT](#) acquisitions per cycle (JPL/NASA, 2019; Biancamaria et al., 2016).

The unprecedented detail of SWOT data is expected to vastly improve our understanding of the dynamics of continental
45 water bodies (Biancamaria et al., 2016) and~~by extent~~, [by extension](#), also of the Carbon (Cole et al., 1994) and Methane (Walter et al., 2007) budget. The dense spatial coverage enables studies of change at a regional scale, such as lake water storage, which is highly variable (Woolway et al., 2020). Importantly, with SWOT, the science objective is to monitor small lakes with an area down to 0.0625 km² (JPL, 2024b) – which represent a significant fraction of global lakes (Taburet et al., 2020) – that previously were too small to be observed by nadir satellite altimetry missions effectively. SWOT ~~certainly~~ provides a more
50 complete picture, enabling a better understanding and thus providing the basis for better decision-making.

~~Laipelt et al. (2025) and Simoes-Sousa et al. (2025) investigate the 2024 Brazil flood using the SWOT raster and the pixel cloud data, respectively, showing SWOT's potential for understanding floods and to estimate water volume~~[Franze et al. \(2025\) investigate how SWOT can facilitate observations of the highly dynamic braided Brahmaputra river](#). Buzzanga et al. (2025) perform a case study on Death Valley, finding SWOT to measure water with unprecedented detail that will improve our
55 understanding of freshwater availability and management in the future. Yu et al. (2024) compares SWOT RiverSP and LakeSP water surface elevations against Hydroweb and G-REALM product data, finding a good agreement, and Wigneron et al. (2024) validates the 1-day (calibration/validation) orbit RiverSP data against other satellite altimeters for river WSE, confirming good preliminary results, and highlighting the unprecedented spatial resolution SWOT provides. Jacobs et al. (2025) show that resid-

ual systematic errors in the SWOT data are detectable relative to nadir satellite altimeters over the ocean, anticipated by Peral
60 and Esteban-Fernandez (2018).

This study investigates the ~~possibilities of constructing~~ feasibility of tracking lake-level anomalies in Denmark by constructing
~~relative~~ WSE time series from SWOT HR PIXC ~~version D data and evaluates them against (version D) data.~~ Using the SWOT
~~LakeSP product as a baseline, we evaluate our workflow against in-situ gauge measurements from~~ 37 ~~gauged lakes with surface~~
~~areas between 40 and lakes spanning a wide size gradient (0.25 to 40 km² and SWOT LakeSP prior time series as a baseline.~~
65 ~~Additionally, we find indications for a residual roll error-).~~ Through this evaluation, we aim to resolve two primary questions:
~~first, how the utilization of lower-level data alters and potentially improves local lake-level monitoring relative to the standard~~
~~LakeSP product; and second, whether residual roll errors remain identifiable~~ in inland SWOT ~~PIXC data on Danish lakes.~~
~~observations. Following this introduction, Section 2 of this paper provides an overview of details~~ the data and study area, while
Section 3 ~~outlines the methods. Results are presented in Section describes the methodology, Sections~~ 4 and ~~discussed in Section~~
70 ~~5. Lastly, we present our conclusion in Section 6. 5~~ present and discuss the findings, and Section 6 concludes the paper.

2 Data and Study Area

2.1 SWOT

The joint CNES and NASA satellite SWOT was launched successfully on ~~December 16, 2022.~~ 16.12.22. It carries a Ka-band
75 radar interferometer as the main scientific instrument. The SWOT mission aims to enhance our understanding of the global
water cycle through measurements of ocean and inland surface water topography. It completed the initial calibration and test
phase and has, since July 2023, been operating in its nominal 21-day science orbit (JPL, 2024b).

Inland water SWOT data is available in various products with different processing granularity. The most detailed information
is available in the KaRIn water mask point cloud L2 HR PIXC data set (JPL, 2023b; SWOT, 2024b). ~~Whereas In contrast,~~ the
L2 HR LakeSP product (JPL, 2023a; SWOT, 2024a) assigns and aggregates the PIXC data to lakes from the "prior lake
80 database" (PLD) (Wang et al., 2023). River data is analogously available in the L2 HR RiverSP product (SWOT, 2024c). Here,
we ~~primarily~~ use the L2 HR PIXC data product version D as it provides the highest degree of freedom. From now on, we will
refer to this dataset exclusively as PIXC. Initial investigations were done with the LakeSP product, but we found some issues
for the small Danish lakes, where the WSE assignment to the PLD geometry resulted in assigning water to areas where no
water is present. We have no reason to doubt the quality of the LakeSP product in other areas and expect it to improve over
85 time.

SWOT sampling geometry is not uniform. The change of incidence angle across track is large, in relative terms, causing
effective pixel spacings of ca. 60m to 10m from close to far range (Fjørtoft et al., 2014). However, as noise levels increase
toward the far-range, near-range observations provide higher data reliability. The along track resolution is fixed at 22m
(JPL, 2023b).

90 We use all PIXC data within ~~57.2°–54.7°~~ -57.2°N and 8.1°–12.6°E. File duplicates are identified by the Composite Release
Identifier (CRID) and product counter. Since the lakes included in the study have a sufficient number of "open water" observa-

tions, we only use class 4 PIXC data, and not "water near land" (class 3). ~~At the time of writing, cycles 20 to 31 had not yet been reprocessed to version D. They are filled with process version C. Overall, SWOT PIXC vD data up to cycle 42, pass 458 (09.12.2025), were used.~~

95 50, pass 180 (16.05.26) was used. We present prior LakeSP data from Hydrocron (Greguska et al., 2025) for comparison with our approach, ~~using time series plots in the "Result" section. Currently, Hydrocron only provides process version C (until 02.05.2025 for Denmark), which we fully utilize.~~ The LakeSP is filtered on $quality_f = 0$, $xovr_cal_q = 0$ or 1, and $dark_frac \leq 0.1$.

2.2 In-situ Gauges

100 In-situ stations measuring lake WSE are available through ~~WSP (2024)~~ Vandportalen (WSP, 2024), combining multiple operator institutions. Most gauges cover the timeframe from the first SWOT 21-day science orbit cycle over Denmark (26.07.23) up to date. The used gauge data has a daily resolution, and the water level is referenced to the Danish height system DVR90. To ~~asses~~ assess SWOT's ability to measure relative WSE change, we remove the median offset between SWOT and the gauge on a per-lake-basis, before reporting any metric. The offset for each gauge is listed in Table A1. The gauge uncertainty depends on
105 the sensor. The water level is mainly measured with pressure and ultrasound sensors, where the uncertainty is listed as 15mm and 5mm-30mm (DMI, 2018).

2.3 Lake Geometries / Masks

The investigated lakes are exclusively located in Denmark and are selected from the 'sø' vector layer product of GeoDanmark (@geodanmark, 2024), documented in GeoDanmark (2018). The data set is updated cyclically every 5 years (KDS, 2024) and
110 contains permanent lakes above 100m² in surface area. Additionally, the set of lakes used in this study is truncated below a surface area of 0.25km², leaving the 228 lakes, presented in Figure 1. The lake geometries are used to extract the relevant PIXC data. The available lake information from GeoDanmark is manually expanded by: annotating lake names, indicating whether a lake possesses a gauge, the gauge's IDs, location, and vertical reference. In total, 37 gauged lakes are used in the comparison. Their surface area distribution is shown in Figure A1D in the Appendix.

3 Methods

3.1 Point Cloud Tile-Management and Masking

Lakes within one cycle and pass can be covered by ~~more than one tile~~ multiple tiles. We, therefore, concatenate all tiles within one unique cycle and pass before further analysis. If a given SWOT pass partially covers lakes, we do not discard ~~it~~ the affected lake from our analysis, as long as it fulfills the selection criteria described in the following subsections. The PIXC data product
120 contains many targets that can have vastly different WSEs at proximity. To minimize their influence, we extract the PIXC observations via the lake mask.

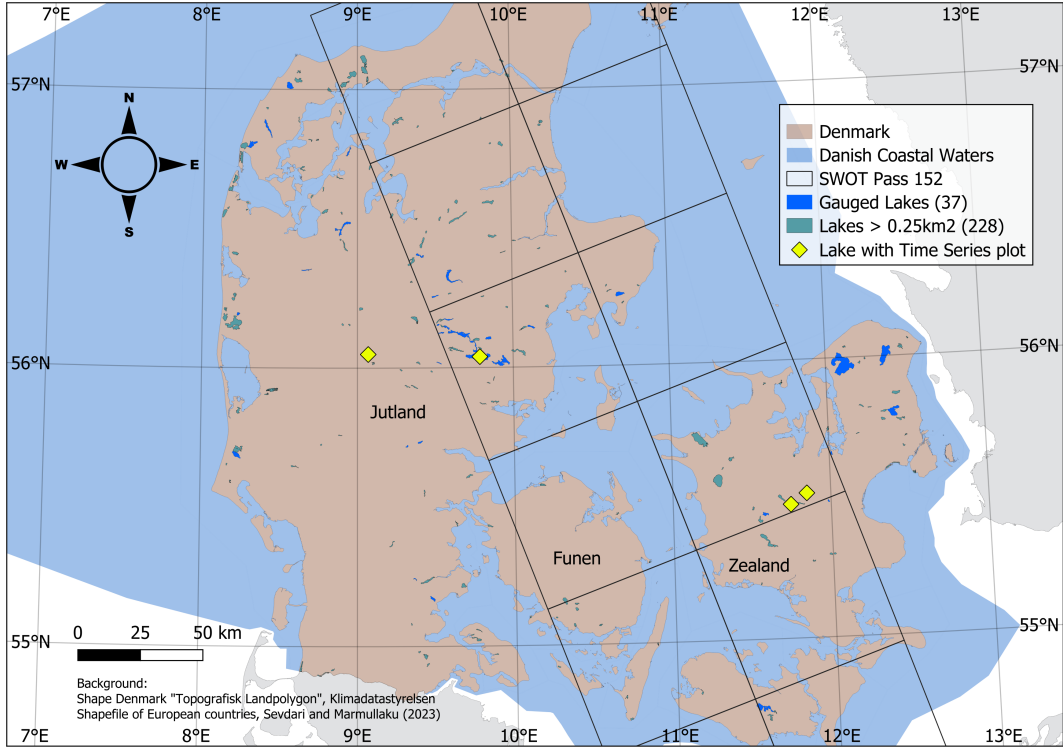


Figure 1. Map of Denmark with lakes larger than 0.25 km^2 . Detailed list of all gauged lakes is provided in Table A1. Danish shapefiles from [@geodanmark \(2024\)](#) [Klimadastystrelsen \(2026\)](#); [@geodanmark \(2024\)](#) and background borders from Sevdari and Marmullaku (2023).

3.2 Water Surface Elevation

The SWOT WSE w.r.t. the EGM2008 geoid used in this work (H_{swot}) is based on points with the "open water" class (JPL, 2023b) through the following expression

$$H_{swot}(P) = h(P) - (T_{solid} + T_{load} + T_{pole})(P) - N_{geoid}(P), \quad (1)$$

125 for one point (P) with the natively reported height (h) given w.r.t. the WGS84 reference ellipsoid (JPL, 2024b), corrected for instrument and crossover calibrations, signal propagation delays due to iono- and troposphere (dry & wet) (JPL, 2023b), all three earth tides (T) [as provided in the PIXC product](#), and the geoid height above the reference ellipsoid (N_{geoid}). Here we apply the EGM2008 geoid model (Pavlis et al., 2012) provided in the SWOT product. [Danish lakes are rarely ice covered in the winter. We therefore chose not to account for potential ice cover.](#)

130 3.3 Water Level Time Series: Data Selection Criteria

To account for outliers that persist after the spatial masking process, we utilise that SWOT surface elevations within one lake are approximately normal-distributed. Therefore, an observation P (one point) is excluded if it is outside the 99.7% confidence

interval

$$H_{swot}(P) \notin [\mu - 3\sigma, \mu + 3\sigma](H_{swot}), \quad (2)$$

with mean (μ) and standard deviation (σ) of the lake surface elevations H_{swot} for the respective acquisition. From this stage,
 135 we defined and tested six data selection criteria to understand which observation points should be used to summarize the WSE
 for the given timestamp. The criteria are presented in Table 1. We chose the median over the mean as the summary measure
 of the water level since it is more robust to outliers that might be missed by previous filtering. The median is applied to all
[points as filtered by the selection criteria \(either all available points or ~~to~~ points without a geo-flag\)](#). Where geo-flag refers to
 the point-wise 32bit geolocation quality flag indicating the quality of variables such as elevation h , latitude, and longitude. We
 140 use the geolocation quality flag over the other available quality flags, as it is the designated quality flag for e.g. *height* in the
 SWOT documentation (JPL, 2023b).

The median WSE for a given timestamp and lake can be discarded based on WSE standard deviation, the number of points
 used for the median, or if too many points are geo-flagged. We found that acquisitions with fewer than 200 points produced out-
 liers in the time series. [We chose the threshold of 200 as an empirical threshold to balance retaining timestamps and removing](#)
 145 [outliers. Refer to Section 5 for further discussion.](#) Generally, no lake is completely discarded based on the data selection crite-
 ria; it is strictly applied to the individual timestamps in the time series. Hence, if one lake’s acquisition is discarded based on
 having fewer than 200 points, only that particular timestamp will be missing in the final time series. [With this threshold, we](#)
[deliberately accept less retained timestamps to trade off for ‘no’ outliers in our timeseries. We do not perform weighting or](#)
[spatial screening beyond the lake mask extraction. A flowchart of the method is shown in Figure A1A in the Appendix.](#)

Table 1. Data selection criteria describing how to aggregate one WSE measure for a given lake and timestamp, and when to discard it. [With](#)
[std: standart deviation.](#)

Selection Criteria	Summary Measure	on which Points	min N of Points for timestamp	std
1	median	all	–	–
2	median	all	200	–
3	median	all	200	≤ 1
4	median	all if max 20% geo-flagged	200	≤ 1
5	median	points without geo-flag	–	–
6	median	points without geo-flag	200	–

150 3.4 Offset and Errors

The SWOT and gauge-based WSE time series have a constant offset, given the different vertical references. In addition,
 the SWOT KaRIn measurements are sensitive to errors in the roll angle and interferometric phase (JPL, 2024b), which are
 addressed in the satellite crossover calibration. Hence, potential errors in the crossover correction might introduce additional,

time-varying errors between the gauge and SWOT-based water level time series, similarly to what has been shown for the ocean (Jacobs et al., 2025). Hence, if present, a remaining roll error at a given time stamp would result in a larger error, between the gauge and SWOT WSE in one side of the swath and a smaller one in the other side. Danish lakes typically have seasonal WSE variations of less than 1m, thus, even minor remaining crossover correction errors would influence the time series. We see the possibility for a time-varying **residual roll error** (ϵ_{roll}) that is a function of the lake's position relative to the ground track of ~~SWOT a SWOT pass~~ – similarly to a "slope". ~~SWOT's errors and in particular also roll error are discussed~~
 error sources, in particular the roll error, are discussed in detail by Peral and Esteban-Fernandez (2018); Peral et al. (2024).

To report sensible metrics for relative WSE change, the constant offset per lake must be removed. The difference in WSE (ΔH) between the gauge (H_{gauge}) and SWOT is given by

$$\Delta H(id, c, p) = H_{gauge}(id, c, p) - H_{swot}(id, c, p), \quad (3)$$

with data for all cycles (c) and passes (p) for the respective lake (id), if gauge data is available and valid surface elevations H_{swot} following the selection criteria of Section 3.3 exist. The constant offset per lake (b_-) is then computed as

$$b_-(id) = median(\Delta H(id, c, p)), \Rightarrow \Delta H' = H_{gauge} - b_- - H_{swot}. \quad (4)$$

The roll error depends on the lake's distance to SWOT's ground track ($d \in [-60, 60]$ km). We use the lake's centroid and define negative distances to the left of SWOT's ground track. If roll errors are present, we expect a correlation between the gauge-SWOT difference $\Delta H'$ and the perpendicular ground track distance (d). ~~The correlation is significant if the~~ We classify the acquisition to have a roll error if the correlation's p-value is ≤ 0.05 . ~~If this is the case and and if the~~ $|PCC| \geq 0.7$, ~~we classify the acquisition to have a roll error.~~ The error budget is superimposed with random noise ϵ_{random} for each lake. The total error is hence conceptually described as

$$\Delta H(id, c, p) = b_-(id) + d \cdot \epsilon_{roll}(c, p) + \epsilon_{random}(id, c, p). \quad (5)$$

We expect the residual roll error to occur only in some of SWOT's acquisitions and to be small. We investigate indications of the error over Danish lakes, while the main focus remains on evaluating SWOT's capability to detect relative WSE changes in small Danish lakes.

3.5 Statistical Evaluation with Gauges

The water level time series are evaluated per lake against gauge data. We are using the Root Mean Square Error (RMSE) and Pearson Correlation Coefficient (PCC) ~~as performance metrics. They are~~ defined as:

$$RMSE = \sqrt{\frac{1}{N} \sum (x_i - y_i)^2}, \quad PCC = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum (x_i - \bar{x})^2 \sum (y_i - \bar{y})^2}} \in [-1, 1], \quad (6)$$

with SWOT estimated water level (x), target offset removed gauge water level (y), and $\bar{x} / \bar{y}$ represent the mean. x is formed from H_{swot} , potentially with added corrections. Danish lakes typically have small seasonal signals (< 1 m in 2023/24), deteriorating the expressiveness of the RMSE. Hence, it is important to consider both RMSE and correlation simultaneously.

4.1 Time Series Data Selection Criteria

The Figure 2 displays the time series for the six defined data selection criteria (Table 1) are shown in Figure 2 for using Valsøllille Sø, a typical Danish lake w.r.t. representative Danish lake regarding surface area and seasonal signal. The offset removed gauge timeseries is exemplary shown for criteria 6. The results for figure includes the offset-removed gauge time series for criterion 6 as an example. Table 2 summarizes the performance metrics across all gauged lakes are summarised in Table 2. Requiring a minimum. Implementing a minimum threshold of 200 observations shows good improvements in RMSE and PCC, while the requirement for the standard deviation shows no improvement. Requiring reduces the RMSE and increases the PCC, whereas the standard deviation threshold yields no metric improvement. Restricting geo-flagged points to a maximum of 20% of significantly improves both validation metrics, while completely excluding geo-flagged points significantly improves the scores. Excluding all geo-flagged points yields similar results performance. Criterion 6 , which requires a minimum of 200 observations per lake and timestamp, performs equally to criterion 4 but does not contain contains no flagged points. Therefore, we adopt criterion 6 for the remainder of this paper as the more conservative criterion. The Finally, the LakeSP time series exhibits good strong RMSE and PCC , values but retains significantly fewer valid timestamps compared to than criterion 6. In the following, we utilized selection criterion 6. We present the development of the metrics over lake surface area from criterion 1 to 6 in the Appendix in Figure A1B,C.

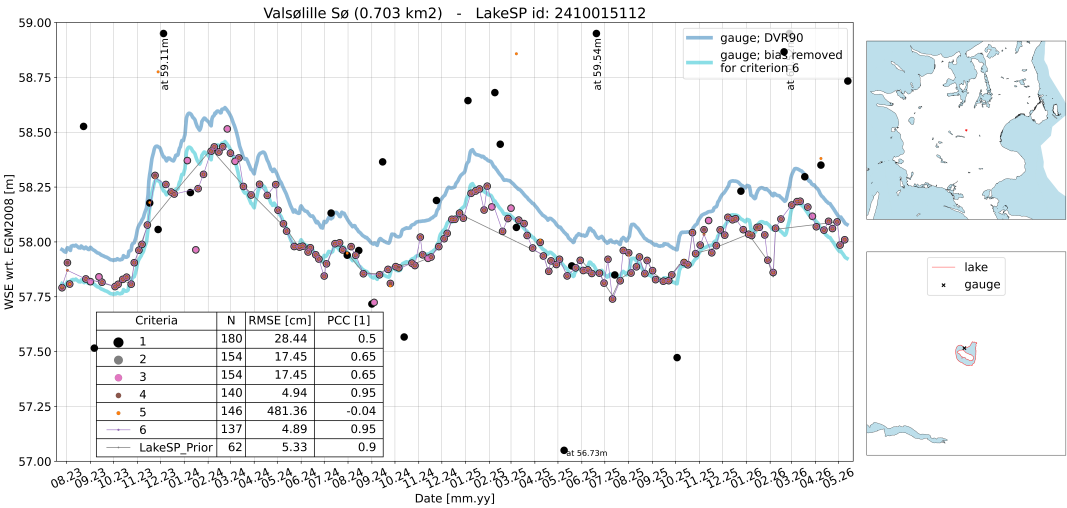


Figure 2. SWOT WSE time series for all 6 defined data selection criteria, exemplary for Valsøllille Sø, with RMSE and Pearson Correlation Coefficient vs. gauge data and the number of timestamps in the respective time series (N). Filtered LakeSP prior data is shown for reference.

4.1 Roll Error

Table 2. Median and 2.5% / 97.5% quantiles of the root mean square error [cm] and Pearson correlation coefficient [1] of all 37 used gauged lakes for the 6 time series data selection criteria. Summary metrics are described in Table 1, [detailed lake specific metrics in Figure A1](#).

Summary metric	1	2	3	4	5	6
2.5% quantile	7.95 6.24	5.74 5.15	4.09 5.15	4.12 4.07	4.14 4.18	4.06
median RMSE	26.76 30.02	13.79 9.98	13.07 9.34	5.16 5.34	7.33 7.73	5.34 5.57
97.5% quantile	618.50 440.27	232.09 140.04	53.58 65.23	17.39 16.47	452.21 514.06	18.37 19.96
2.5% quantile	-0.06 -0.09	0.00 -0.03	0.10 0.13	0.37 0.42	-0.13 -0.12	0.36 0.42
median PCC	0.42 0.44	0.57 0.65	0.63 0.76	0.93 0.92	0.81 0.76	0.91
97.5% quantile	0.94 0.97	0.97 0.98	0.98	0.99	0.99	0.99

Figure 5A Figure 3 presents three offset-corrected water level time series alongside the corresponding LakeSP time series. Søby Sø (0.709 km² surface area, Figure 3B) exhibits minimal WSE amplitude and a low correlation. Conversely, Tivolisøen (0.269 km² surface area, Figure 3A) – the smallest gauged lake in this study – has a WSE amplitude exceeding 150cm, an RMSE of 6.82cm, and a PCC of 0.99. Mossø (16.569 km² surface area, Figure 3C) represents a large lake in the Danish context and shows a low RMSE and a high SWOT-to-gauge correlation. Figure A1E displays a linear relationship in a gauge vs. SWOT scatter plot for Mossø. Our processing approach yields a median RMSE of 5.57cm and a median PCC of 0.91 across all 37 gauged lakes. For comparison, the filtered LakeSP dataset achieves a median RMSE of 4.92cm and a median PCC of 0.94. In contrast, filtered LakeSP retains a median of 60 timestamps over the nearly 3 years investigated, while our approach retains a median of 125 timestamps (mean: 62.8 vs. 118.9). Figure 4 shows the metrics and retained timestamps for our approach vs LakeSP against lake surface area and WSE amplitude. Table A1 lists the detailed metrics for all lakes.

At the latitude of Denmark, SWOT provides higher temporal resolution than most traditional satellite altimeters. Across the 228 Danish lakes exceeding 0.25 km², SWOT covers 54.63% of the lakes with 4 passes per cycle, 22.47% with 3, and 22.9% with 2, yielding an average of 3.3 passes per cycle. After accounting for 42 inaccessible acquisitions out of 417, the effective temporal resolution averages approximately 9.5 days. Downsampling the in-situ gauge WSE time series to this 9-day resolution produces a median correlation coefficient of 0.96 (2.5%/97.5% quantiles: 0.63/0.99) and explains 0.92 (2.5%/97.5% quantiles: 0.40/0.99) of the observed variability.

4.1 Residual Roll Error

To address our second research question, if SWOT inland water data contains residual roll errors, we present Figure 5A, which shows the height difference $\Delta H'$ between the offset-removed gauge and SWOT ($\Delta H'$) for lakes observed by pass 152 over all cycles. Up) between the offset-removed gauge data and SWOT observations for lakes across all cycles of pass 152. SWOT observes up to 19 lakes are observed by SWOT in this pass. The number might be lower in the individual cycles due to the selection criteria. In this pass, SWOT observes, though data selection criteria reduce this number in individual cycles. This pass captures lakes in two hydrologically separate areas. Lakes in Jutland are shown in blue and regions: blue markers designate lakes in Jutland, and red markers designate lakes outside Jutland in red. All lakes outside of Jutland are Jutland lie to the left of the SWOT

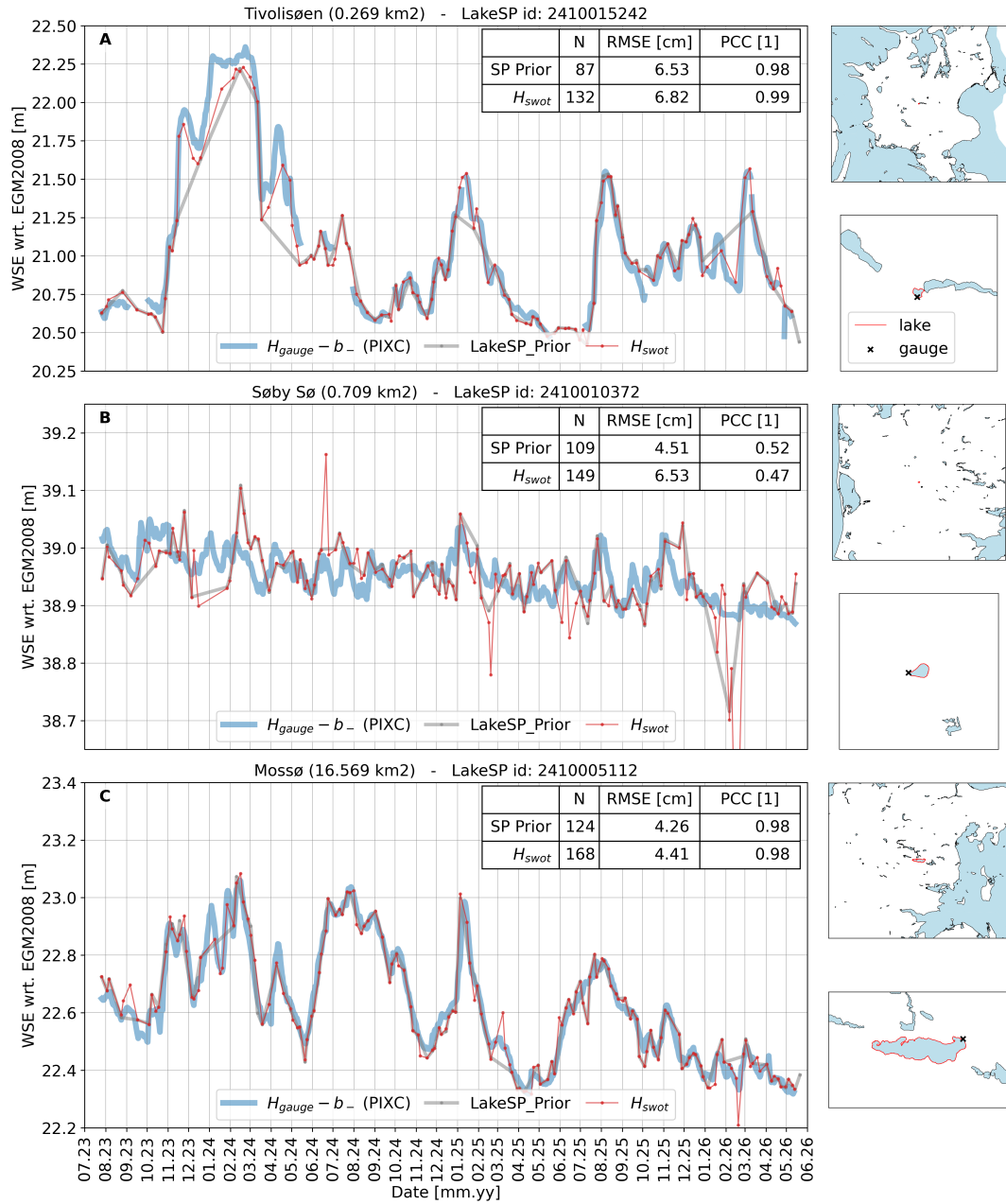


Figure 3. Water surface elevation time series for three typical Danish lakes. Offset removed gauge data is shown in blue, our SWOT approach in red, and filtered SWOT LakeSP Prior time series are shown in the background for comparison. A shows Tivolisøen, the smallest lake in this study. B shows Søby Sø, a lake with minimal variation in water surface elevation. C shows Mossø, the third largest Danish lake.

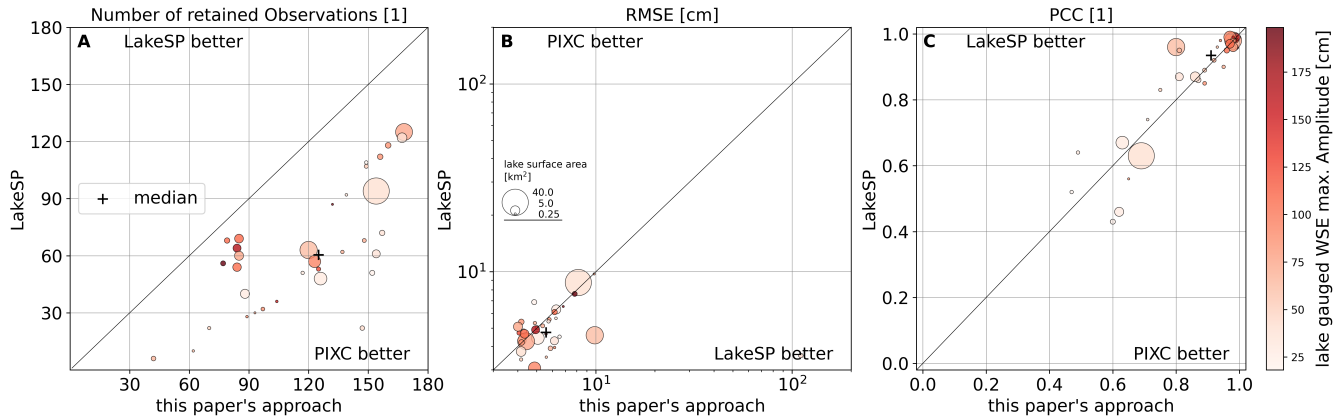


Figure 4. Metrics and retained timestamps for this paper’s approach and filtered LakeSP from Hydrocron. The circle size indicates lake surface area and the color indicated the maximum gauge WSE amplitude over the investigated timeframe.

ground track, ~~while-whereas~~ all but one Jutlandic lake ~~are lie~~ to the right of SWOT’s ground track. The distribution of ~~the $\Delta H'$ as a function of cycle is generally centered~~ distribution across cycles generally centers around zero, ~~yet some cycles display certain cycles exhibit~~ a slight offset. ~~Cycles Gray bars highlight cycles~~ with a significant roll component ~~are highlighted by a gray bar. Here, where~~ the $\Delta H'$ distributions for lakes in the right and left ~~swath of SWOT show considerable differences.~~

Three cycles with a significant roll component are shown in detail in Figure 5B–D, plotting ~~swaths differ considerably. Figures 5B–D plot $\Delta H'$ as a function of against~~ the distance to SWOT’s ground track the SWOT ground track for three specific cycles containing a significant roll component. The slope ~~is not constant over time and can change~~ varies across cycles and reverses direction. We use the 1σ spread of the ~~time stamp’s $\Delta H'$ distribution — (shown in green in each plot — as a measure for —)~~ to quantify the roll error amplitude.

Figure 6A ~~analogously shows SWOT’s error vs. gauge data displays the SWOT-to-gauge error~~ for all passes covering Denmark. ~~The Green and blue elements indicate the median $\Delta H'$ and 1σ quantile spread (84.15% – 15.85% quantile) are shown in green if the acquisition has a significant roll error component and in blue if not. For two acquisitions without)~~ for acquisitions with and without a significant roll error, ~~$\Delta H'$ over d are shown Figure A1G and H. Only acquisitions with a minimum of 10 observed lakes are shown with median and quantile spread to component, respectively. To minimize random effects. Of the 127~~

acquisitions with, the plot only includes the median and quantile spread for acquisitions capturing at least 10 ~~or more lakes, 23 (ca. lakes. Out of 160 such acquisitions, 29 (approximately 18%) have exhibit~~ a significant roll error component. Figure Figures A1G and H show $\Delta H'$ versus distance (d) for two acquisitions lacking a significant roll error; a slope is nevertheless visible. Figures 6B and D ~~show present~~ the median of the absolute $\Delta H'$ distribution for acquisitions with and without a significant roll error component. ~~Both are within margin; both medians remain close~~ to each other for the lakes investigated in this study. Figure investigated lakes. Figures 6C and E show the distribution of the 1σ quantile $\Delta H'$ spread for roll and no roll error component. As expected, the comparison reveals a more extensive ~~these two categories, demonstrating a wider~~

spread for acquisitions with a significant roll error component. Aggregating Figure 6B and D, the median $|\text{median}(\Delta H')|$ for all acquisition distributions is 2.15. Aggregating these distributions yields a median $|\text{median}(\Delta H')|$ of 1.79cm. The spread for all acquisitions based on Figure 6C and E across all acquisitions has a median of 5.68cm, but ranges to 11.29cm for 5.43cm and reaches 12.60cm at the 0.95 quantile.

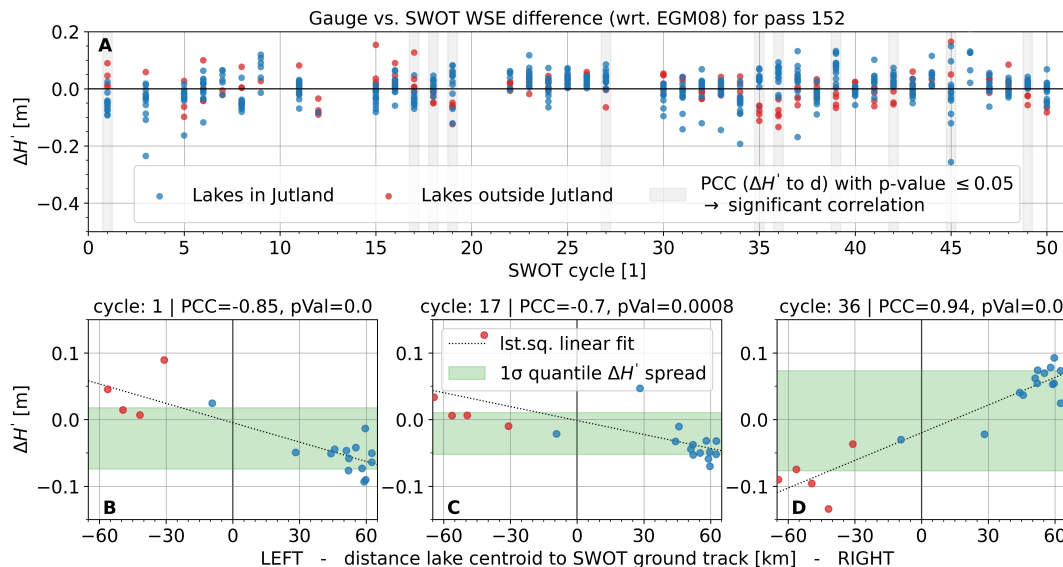


Figure 5. A: $\Delta H'$ (SWOT vs. gauges) over time for all lakes in pass 152. B-D: expanded plot of SWOT's error per lake over lake's centroid distance to SWOT's ground track. Negative distances are left and positive to the right of SWOT. Exemplary for the cycles 1, 17, and 36.

5 Discussion

5.1 Final Time Series Three water level time series plots corrected for the constant offset are shown in Figure 3 along with LakeSP-based time series. Søby Sø (0.709km² surface area, Figure 3B) is an example of a lake with minimal WSE amplitude. The correlation is poor, SWOT Sampling Geometry and the Data

The cross-track variation in SWOT's sampling geometry directly influences the operational performance of our 200 observation threshold. Because near-range pixel spacing is significantly larger (≈ 60 m) than far-range spacing (≈ 10 m), small lakes located in the near-range inherently yield fewer PIXC observations per pass, making the 200-point threshold harder to satisfy. Conversely, near-range observations benefit from lower noise levels and higher individual point reliability. While implementing an adaptive threshold based on a lake's WSE signal appears to be inside of SWOT's error budget, cross-track position could potentially maximize temporal resolution, we chose to favor a uniform threshold to maintain pipeline simplicity and interpretability. Given that our uniform filtering approach already preserves a higher temporal resolution than the standard filtered LakeSP product, we think this choice is justified.

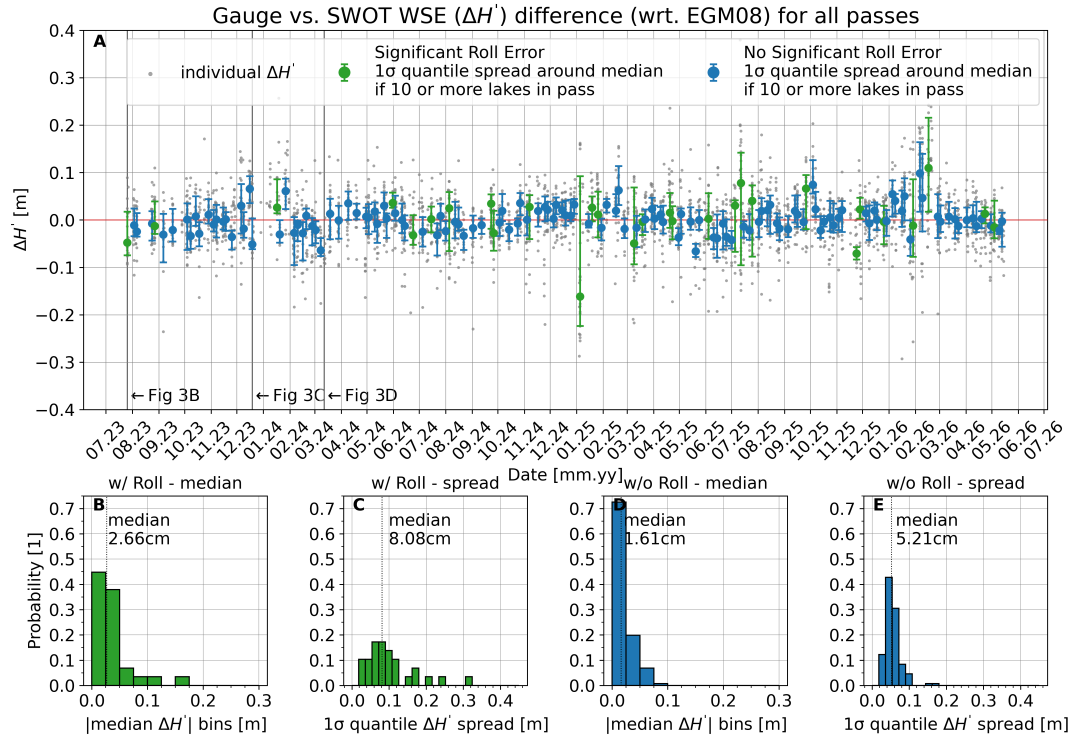


Figure 6. A: $\Delta H'$ (SWOT vs. gauges) over time for all passes and all lakes in Denmark. For timestamps with ≥ 10 observed lakes, the median and 1σ quantile spread (0.1585 to 0.8415) are shown. If $\Delta H'$ significantly correlates with distance to SWOT's ground track (d), it is shown in green, otherwise in blue. The three vertical lines indicate the timestamps with detailed correlation plots in Figure 5B-D. B: distribution of the absolute median $\Delta H'$ for timestamps with significant roll error. C: distribution of the 1σ quantile spread for timestamps with significant roll error. D: distribution of the absolute median $\Delta H'$ for timestamps without significant roll error. E: distribution of the 1σ quantile spread for timestamps without significant roll error.

Similarly, our decision to restrict data extraction to the "open water" classification may limit analysis of small or narrow, elongated lakes, which naturally exhibit a higher proportion of "water near land" pixels. However, our results demonstrate that this constraint does not introduce a significant disadvantage at the spatial scales investigated in this study. For instance, Tivolisøen (0.269km² surface area, Figure 3A) is the smallest gauged lake in the study and has a WSE amplitude above 150cm. Despite its size, RMSE (7.10cm) and PCC (0.99) are satisfactory, proving SWOT's capabilities. Mossø (16.569km² surface area, Figure 3C) represents a large lake in the Danish context. Here, an overall good SWOT to gauge correlation and a small RMSE is found. For Mossø, we exemplarily present a gauge vs. SWOT correlation scatter plot (Figure A1E), showing a linear correlation. For the Danish lakes considered in this study, the LakeSP time series generally shows similar performance to our approach, but retains fewer valid timestamps over the same time period. A detailed list is provided in Table A1. Lakes with high RMSE for the LakeSP data have an outlier that was not removed by the filtering deployed in this study.

The median RMSE for all this study, Figure 3A) and Valsøllille Sø (an irregularly shaped lake, Figure 2) display robust performance metrics that align well with the overall median of the 37 gauged lakes is 5.34cm with a median PCC of 0.91. Detailed metrics for all lakes are listed in Table A1 and shown in Figure A1A and B in the Appendix. For comparison, the median RMSE for the filtered LakeSP is 6.05cm, and the median PCC is 0.89. The filtered LakeSP (until 02.05.2025) retains a median of 35 timestamps per lake compared to 65 for our data selection criteria. For the whole period until 09.12.2025, our approach retains a median of 98 timestamps for a given lake, shown in Figure A1C investigated lakes, confirming the "open water" restriction to be viable for local lake level monitoring within our study's size and hydrologic domain.

5.2 Performance and Limitations

The aim of this study is to assess SWOT's capability to capture relative changes in WSE in small Danish lakes, rather than absolute elevations. To derive the relevant metrics, we removed the median offset between SWOT and gauge measurements (b_{-}). This adjustment is sufficient for evaluating SWOT's performance in detecting relative WSE changes. Consequently, investigating the origin of the removed offset lies beyond the scope of this study.

Water surface elevation time series for three typical Danish lakes. Offset removed gauge data is shown in blue, our SWOT approach in red, and filtered SWOT LakeSP Prior time series are shown in the background for comparison. **A** shows Tivolisøen, the smallest lake in this study. **B** shows Søby Sø, a lake with minimal variation in water surface elevation. **C** shows Mossø, the third largest Danish lake.

6 Discussion

5.1 Spatial Masking and LakeSP

This study aims to investigate the relative WSE change. A static lake mask is sufficient for this. If the lake extent expands, the geometry would only mask open water. If the lake shrinks/ disappears/ moves, the mask will include land. Criterion 6 matched the performance of criterion 4 while eliminating flagged data. We chose to adopt it as the more conservative selection strategy for this paper. By doing so, we aim to reflect the importance of producing accurate WSE measurements that are not contaminated by outliers. Our experiment's results highlight the critical trade-off between standard data products and customized lower-level processing. While the operational LakeSP product provides accurate WSE estimates with slightly better metrics, our filtering approach for the HR PIXC data preserves substantially more valid timestamps, thereby maximizing the temporal resolution necessary for robust local lake monitoring and other hydrologic applications. Especially for lakes with highly variable WSE patterns: even in Tivolisøen (Figure 3A) peaks in WSE (11.23-02.24; 03.24-05.24; 01.26-03.26) are completely missed by filtered LakeSP, too. However, since we only use SWOT's but retained by our approach. This demonstrates that, despite similar metrics, our approach displays a clear advantage over LakeSP, given its higher temporal resolution.

While both our approach and the baseline LakeSP product aggregate WSE values from the SWOT PIXC product, two methodological choices separate the pipelines. First, LakeSP includes "dark water" and "water near land" pixels, whereas we restrict extraction strictly to the "open water" ,SWOT's native land exclusion should handle this case. Our requirement for a minimum of 200 points per lake and acquisitions should exclude timestamps with too few observations to form a robust WSE summary. In principle, a dynamic mask would be ideal. If it is inaccurate, however, it might introduce noise, as presented in Figure A1F in the Appendix. Measurements of secondary lakes near the target can have significantly different WSE, necessitating robust filtering. Nevertheless, for global applicability, the approach chosen for the LakeSP product should be preferred.

If the LakeSP product is filtered as described above, the LakeSP time series exhibits mostly good RMSE and PCC values, despite the discussed assignment problem. However, this is achieved at the expense of discarding many timestamps that our approach retains, yielding similar or slightly better RMSE and PCC results. For use cases class. Second, LakeSP dynamically adapts the initial Prior Lake Database mask instead of utilizing a static mask. Specifically, "dark water" observations often carry higher noise levels, and the dynamic mask can inadvertently expand over shoreline features – such as wet soil – misclassified as water (Figure A1F). By relying on a static mask and open-water pixels, our method circumvents these noise and misclassification pathways, reducing non-water artifacts and thus preserving a greater number of valid timestamps.

For global use cases or applications, where the temporal resolution is not of the highest priority, but ease of use and computational resources are, we see LakeSP as preferable. The same applies to global products. Quarrying Querying LakeSP from Hydrocron takes seconds per lake. Quarrying the pre-processed aggregated WSE timeseries for a lake from Querying commuted lake level values from our approach from a local database requires a similar time. Pre-processing requires between one and is comparable to that. However, computing the PIXC data takes about one to two minutes per SWOT pass over Denmark, depending on the number of lakes observed. If the method does not change, this computation – this has to be done only once. Additionally, we need to highlight the different baselines of PIXC to Hydrocron LakeSP. The comparison's details will certainly change with an updated LakeSP baseline; however, the overall conclusion we presented in this paper is consistent with a comparison using only PIXC version C we performed previously. Thus, we have no reason to doubt the presented comparison. Given the rapid advances in SWOT processing, these mismatches can not be avoided.

5.1 Time Series Data Selection Criteria

The results of the data selection criteria showed that the most significant RMSE improvements were achieved from two criteria: 1) requiring a minimum number of SWOT points per acquisition and lake, and 2) posing requirements to In the presented timeseries (Figure 3), the geo-quality-flag. On the other hand, the PCC did not improve significantly from criteria 1 to 2. The overall improvement is mainly attributed to the requirements posed on poor correlation observed at Søby Sø indicates that the lake's small WSE seasonal signal falls within the SWOT error budget. In contrast, the geo-flag. It appears that the minor seasonal WSE variations characteristic of Danish lakes can not be resolved appropriately without using the geo-quality-flag. Additionally, the marginal difference between criteria 4 to 6 indicates that up to 20% geo-flagged points are not enough to degrade aggregated WSE, at least for the lakes considered here. However, at a conservative choice we recommend to exclude

all-geo-flagged observations unless the total number of points drops below 200. strong performance metrics at Tivolisøen demonstrate SWOT's capability to successfully monitor very small water bodies when they exhibit a high dynamic range. This shows, that a smaller lake surface area does not automatically result in worse mapping performance; the lake's annual hydrological amplitude must be considered concurrently.

This study limited the SWOT observations to the "open-water" class, which was sufficient for the lakes investigated in this study. For smaller lakes than those investigated here, it might also be beneficial to consider the "water near land" class. The selection criteria could be further improved by investigating the relationship between individual geo-quality-flags and time series outliers to retain even more valid observation points, as in Bazzi et al. (2025) for the raster product. We were unable to establish a clear relationship in a preliminary investigation. Besides the geo-quality-flag, SWOT provides four additional sets of quality flags that could be used in a model approach. In our preliminary study, we could not observe any added benefit of using other flags besides the geo-quality-flags.

5.1 Performance on Danish Lakes

5.0.1 Timeseries

The aim of this study is to assess SWOT's capability to capture relative changes in WSE in small Danish lakes, rather than absolute elevations. To derive the relevant metrics, we removed the median offset between SWOT and gauge measurements (b_{-}). This adjustment is sufficient for evaluating SWOT's performance in detecting relative WSE changes. Consequently, investigating the origin of the removed offset lies beyond the scope of this study.

The median RMSE of all The analysis on the temporal coverage of SWOT over Danish lakes highlights SWOT's capability to resolve the majority of WSE variations across the 37 lakes in this study of 5.34cm, with median PCC of 0.91 is a promising outlook of SWOT's ability to monitor relative WSE changes in small lakes in Denmark and similar regions. Especially considering its high temporal resolution, discussed in the next section. From the three time series shown in Figure 3 we can additionally outline, that a smaller lake area does not necessarily result in worse WSE mapping. The lake's annual amplitude must be considered, too.

5.0.1 Temporal Resolution

At the latitude range of Denmark, SWOT improves the temporal resolution compared to most traditional satellite altimeters. Of the 228 Danish lakes above 0.25km², 54.63% are covered by 4 SWOT passes per cycle, 22.47% by 3, and 22.9% by 2, resulting in an average of 3.3 passes per cycle. Accounting for missing acquisitions (we were unable to access 35 out of 417 acquisitions), the average temporal resolution is 9.5 days, slightly less than the theoretical best if all timestamps were provided and would result in a valid WSE value according to our selection criterion. While missions such as studied lakes. While traditional missions like Sentinel-6, Jason, etc. achieve a or Jason also achieve 10-day temporal resolution, their spatial resolution is limited to their their reliance on 1D ground tracks, which sets a natural threshold to the number of lakes that are measured. SWOT's groundbreaking feature is observing even small lakes at high temporal frequencies. ground tracks inherently limits

the number of observable lakes. In contrast, SWOT's groundbreaking 2D imaging capability allows it to monitor small lakes at high temporal frequencies that were previously unreachable. By successfully capturing these dynamics, SWOT advances our understanding of small lake hydrology and provides essential, high-resolution data to support water resource management for both policymakers and local communities.

~~Downsampling-gauge-WSE-time-series~~

5.1 Spatial Masking

A potential limitation of our proposed workflow concerns the reliance on a static water mask, as the resulting time series depend on the initial mask quality and the degree of seasonal variation in a lake's surface area. While Denmark features high-quality baseline masks and relatively stable lake extents, we evaluated this dependency by artificially expanding and shrinking the target lake polygons by 20 m. This buffer adjustment simulates both spatial uncertainties in the base mask and seasonal fluctuations in lake boundaries.

Modifying the polygons shifted the median RMSE from the baseline of 5.57 cm to 5.18 cm for the +20 m expansion and 5.02 cm for the -20 m contraction. The median PCC adjusted slightly from 0.91 to a 9-day-resolution yields a median correlation coefficient of 0.96 (2.5%/97.5% quantiles: 0.62/0.99), explaining 0.92 (2.5%/97.5% quantiles: 0.38/0.99) of variability. This demonstrates SWOT's ability to resolve most lake WSE variations in the 37 Danish lakes studied, advancing our understanding of small lake dynamics and providing vital insights for policymakers and communities. 0.92 in both scenarios, while the median number of retained timestamps remained nearly constant, moving from 125 to 126 and 125, respectively.

These minor variations suggest that the workflow is relatively insensitive to moderate boundary adjustments, indicating that a static mask may suffice despite spatial uncertainties or typical seasonal variations. This resilience likely demonstrates that SWOT's intrinsic water classification effectively excludes non-water pixels. Nevertheless, we suggest caution when applying a static mask to highly dynamic hydrological regimes, e.g. where lakes regularly dry out completely or double in surface area.

For such highly dynamic environments, users could incorporate a dynamic lake mask into the pipeline without encountering structural conflict. This modification would require a temporal matching routine to pair each SWOT acquisition with the closest available lake mask in time, while keeping a static mask as a fallback option. However, a notable downstream implication involves error propagation, as high spatial uncertainty within a dynamic mask can directly distort the aggregated WSE estimate. Excessively unstable masks, such as the example shown in Figure A1F, could introduce significant error; therefore, we recommend that users only implement water masks they are confident in to prevent introducing artificial noise into the final time series.

5.2 Roll Error

The distinct geographical distribution of the Danish lakes relative to ground track 152 enables the clear detection of systematic spatial effects within the inland SWOT PIXC data. Lakes outside Jutland lie almost exclusively in the left swath and Jutlandic lakes largely occupy the right swath, a cross-track tilt manifests as a vertical discrepancy between the two regions. Based on the lakes investigated in this study and the examples shown in cases examined in Figure 5 and 6, we find indications of a residual

roll-error-component-present-in-inland-SWOT-PIXC-data observe temporal variations in both the magnitude and direction of this slope. As the sign of the slope is time dependent, illustrated with the cycles of pass 152, we may rule out that the observed slope is related to varies across cycles, we can rule out static reference surface issues as this would be, which would otherwise remain constant in time. With the setup of this study, we can not directly quantify the amplitude of the

We are not trying to correct or quantify the residual roll error, given that random error additionally affects the slope. However, for the lakes investigated in this study, the roll error might be up to $\approx \pm 10\text{cm}$ near the edge but only want to investigate its existence. Our set-up is not capable to robustly quantify it and perform an in-depth quantitative analysis of its amplitude. This is out of scope for our study and necessitates a dedicated research paper. However, our results clearly demonstrate its presence. Approximately 18% of the acquisitions exhibit a tilting effect, suggesting that residual roll errors regularly affect inland SWOT data products. Crucially, while this roll component does not significantly alter the overall median error of a given pass, it degrades spatial precision by expanding the overall 1σ spread of the data distribution, with noticeable deviations appearing near the far-range edges of the swath—for example, in Figure 5D.

The residual roll error can likely be ignored for lakes and other Consequently, while researchers can likely ignore this effect for water bodies with large WSE variations. Yet, the error, the tilt may influence the accuracy of WSE time series for water bodies with small WSE variations. We think it will be detrimental for future studies using SWOT to be aware of potential residual roll error component and to make lakes with small seasonal signals. More significantly, measurements of WSS could be superimposed with the residual roll error. Rivers perpendicular to a SWOT ground track would be particularly affected. We think, future SWOT users should maintain awareness of this potential error component. To mitigate this issue, researchers could estimate and correct for the tilt using linear approximations derived from gauge networks or virtual stations distributed across both swath sides. Ultimately, while future SWOT processing baselines will likely improve upon this issue, current applications require a deliberate choice whether addressing it is necessary or not. The on whether addressing this residual roll error could be estimated, modeled, and corrected for using either gauge stations or virtual stations at large lakes for their respective use case.

5.3 Transferability

We established successfully, that our lower-level data approach can improve local lake level monitoring and that residual roll errors are present. To move beyond the circumstances of Danish lakes, we want to discuss in the following, how we foresee various environmental and geomorphological circumstances affect our processing pipeline.

Geomorphology impacts our approach in two distinct ways: first, tall flanking topography creates radar layover, which the SWOT intrinsic DEM masks, thereby reducing the number of valid observations per timestamp and potentially forcing our filter to reject lake observations that fall below the 200-observation threshold. Second, significant WSE differences along a lake's extent complicate the use of a single aggregated WSE value, introducing a sampling bias depending on where the lake was sampled by the retained SWOT pixels. While this effect remains negligible for small lakes, researchers likely should exclude extremely elongated lakes in mountainous terrain from this lower-level data approach.

430 Furthermore, seasonal frozen conditions alter surface properties, as ice cover degrades radar coherence, reducing the density of reliable observations and lowering overall data quality compared to open water, though the precise Ka-band scattering mechanisms over ice and snow warrant further investigation (Christoffersen et al., 2026).

Conversely, submerged vegetation and turbid water do not affect the WSE measurements because the Ka-band SAR signal does not penetrate the water surface, while surrounding canopy cover only blocks penetration along the immediate shoreline, functionally mirroring a slightly undersized lake polygon or the "water near land" class which we did not use in this paper.

435 Meteorological factors also modulate data quality, where wind conditions directly control radar backscatter intensity through an interplay of surface roughness, Ka-band wavelength, and satellite look angles; backscatter typically increases at wind speeds up to approximately 3m/s but decreases beyond this threshold (Fjørtoft et al., 2014), hence, in high wind regime environments, we expect worse data quality.

440 Changing hydrological regimes may impact SWOT measurements. The static lake mask could cause error by including land. However, we expect the impact to be small as we (i) use SWOT's intrinsic water classification by using 'open water' only and (ii) using the median to aggregate a unified WSE measure per lake and time stamp – dampening the impact of outliers. We confirmed this in the mask expansion experiment. At the same time, if seasonal WSE signal is highly variable, higher temporal resolution increases in importance, which is where our approach retains more time stamps than filtered Lake SP.

445 Finally, regarding the transferability of our 200-observation threshold, heterogeneous shorelines affect our pipeline similarly to LakeSP but do not cause significant degradation when paired with an accurate lake mask. Using all 10 passes covering Denmark, our Danish lake dataset samples across the entire swath, hence cross-track positioning does not limit transferability; instead, we see steep terrain remaining as the primary operational bottleneck due to topographic observation loss. For applications targeting smaller lakes that intrinsically yield fewer pixels, users can easily adapt this pipeline by relaxing the 200-observation threshold or incorporating the "water near land" data classification. ~~A linear approximation could be fitted with as few as~~
450 ~~2 stations on either side of SWOT. However, Figure 5B–D shows SWOT's increased error in the far range. This has to be considered when attempting to correct for the roll error component. Overall, more research is required, and future SWOT processing baselines likely will improve on this issue.~~

6 Conclusions

~~This study investigated how SWOT~~

455 ~~This work demonstrates that lower-level SWOT HR PIXC data can be used to generate high-accuracy WSE time series for Danish lakes between 0.25km² and 40km² surface area and capture their relative WSE change. By aggregating meta-information for successfully leveraged to generate highly accurate relative water surface elevation (WSE) time series over small lakes. Based on a comprehensive validation baseline of 37 gauged lakes, we established a robust validation dataset for Denmark, providing a solid foundation for evaluating the performance of SWOT's altimetry data over the time span in Denmark evaluated~~
460 ~~from July 2023 to December 2025. We demonstrated that our method performs slightly better than filtered LakeSP data, while retaining more SWOT observation timestamps. Time series based on our approach capture relative WSE change May 2026.~~

our customized PIXC processing workflow captures relative WSE variations with a median RMSE of ~~5.34 cm and 5.57 cm~~ and a PCC of 0.91 ~~across all 37 lakes. We found a significant roll error component in about~~. While the operational LakeSP product delivers a marginally lower median RMSE (4.92 cm), our approach offers a distinct advantage by retaining roughly twice as many valid observations (a median of 125 versus 60 timestamps). This significantly increased data retention preserves high-frequency hydrological variations that the standard products misses over Denmark. Consequently, future SWOT users should align their dataset selection with specific application requirements, carefully balancing operational simplicity against the desired temporal frequency of water level observations.

Additionally, we demonstrate the existence of a residual roll error in inland SWOT data, which affects approximately 18% of all acquisitions with 10 or more lakes. Without a systematic setup, a quantification of its amplitude is not possible. However, we presented instances for Danish lakes where the residual roll error reaches up to $\pm 10^\circ$ the passes over Denmark. Although our experimental setup was not designed to robustly quantify the absolute amplitude of this error – warranting further dedicated research – SWOT users should remain aware of its presence and adapt their workflows accordingly. This artifact is particularly critical to consider when analyzing lakes with low hydrological amplitudes or when monitoring water surface slopes in rivers aligned perpendicular to the SWOT ground track.

Overall, The transferability of our approach beyond the specific hydroclimatic conditions of Denmark is feasible. Filtering thresholds can be adjusted and dynamic water masks can be integrated to accommodate more morphologically or hydrologically variable environments. Ultimately, SWOT provides unprecedented data, enabling the construction of ~~high-temporal-resolution and high-accuracy~~ high-temporal-resolution and high-accuracy WSE time series that were previously unattainable. This capability is especially impactful for ~~smaller lakes, small water bodies, many of~~ which are now ~~likely~~ observed by a satellite altimeter for the first time – due to SWOT’s broad spatial coverage, ~~compared to traditional satellite altimeter’s ground track data, which effectively overcomes the limitations of traditional nadir altimetry.~~

Data availability. Our data is hosted at DTU DATA (Köhn and Nielsen, 2026). The complete processed SWOT data set with all auxiliary information is available as a SQL source file. We used MariaDB 11.3 and HeidiSQL 12.6 for set-up and management, and the Python mariadb package for access. Data associated with Table A1 are available as separate EXCEL files.

Raw SWOT HR PIXC data (SWOT, 2024b) was downloaded using the Python `earthaccess` API (Barrett et al., 2024). Gauge data was accessed via Vandportalen (WSP, 2024) and SWOT HR LakeSP Prior data via the Hydrocron API (Greguska et al., 2025). Lake vector geometries for masking SWOT data are taken from Geo Danmark 60 (@geodanmark, 2024) documented in GeoDanmark (2018).

Appendix A: Supporting Figures

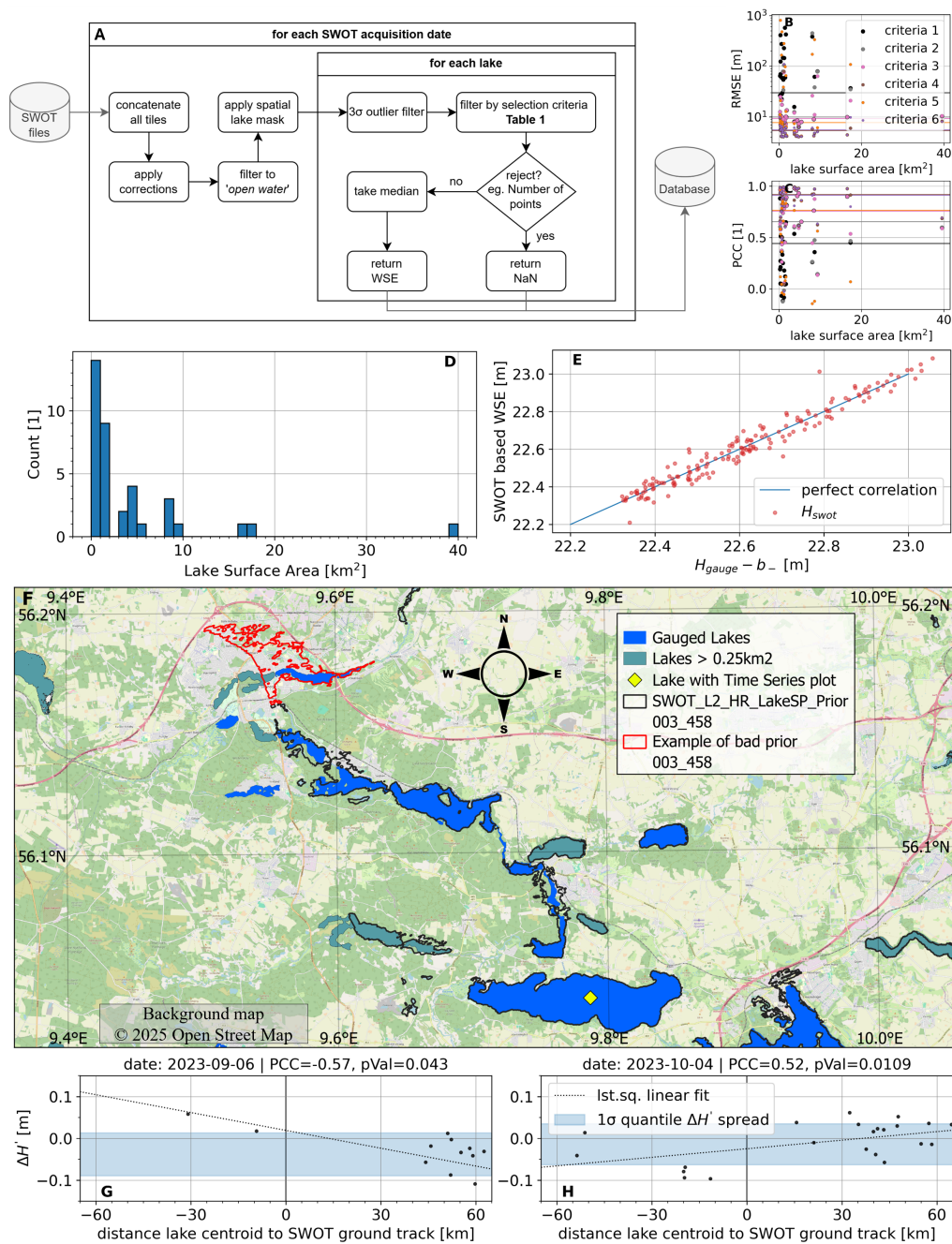


Figure A1. **A** and **C**: flowchart of method pipeline. **B** and **C**: RMSE and PCC for SWOT vs. bias-removed gauge WSE for our approach and filtered LakeSP Prior. Using all available lakes. **C**: valid SWOT time stamps retained for our approach and the filtered LakeSP prior all selection criteria over lake surface area. **D**: distribution of lake surface area of all 37 lakes in this study. **E**: correlation scatter plot for Mossø, shown in Figure 3C. **F**: Example of prior problem in LakeSP for Danish lakes around Viborg. **G** and **H**: Example of two acquisition without significant residual roll error: error over distance to SWOT ground track.

Table A1. List of all used gauged Danish lakes (~~lager~~larger than 0.25 km^2) †: Lake with time series plot. *: relative metrics for H_{swot} (this paper’s approach). **: relative metrics for LakeSP Prior (a dedicated offset is computed). b_- : gauge offset wrt. H_{swot} . N: number of SWOT based time series timestamps; for PIXC ~~until 09.12.25~~ and ~~for~~ LakeSP until ~~02.05.25~~15.05.2026. Δ WSE: max. amplitude of WSE from gauge data.

name	LakeSP id	Area	gauge lon & lat		b_-	Δ WSE	RMSE [cm]		PCC [1]		N [1]
N=37		[km ²]	[deg]	[deg]	[cm]	[cm]	*	**	*	**	*
Arresø	2410015352	39.547	12.0403	55.9778	17.06 <u>16.97</u>	40.2	8.14	8.24 <u>8.76</u>	0.71 <u>0.69</u>	0.7 <u>0.63</u>	123 <u>154</u>
Brabrand Sø	2410005882	1.459	10.0888	56.1477	20.88 <u>22.43</u>	198.5	7.52 <u>7.8</u>	9.0 <u>7.62</u>	0.99	0.99 <u>0.96</u>	61 <u>77</u>
Brassø	2410004442	1.215	9.5591	56.1472	12.42 <u>12.47</u>	40.1 <u>43.3</u>	89.26 <u>110.81</u>	11.99 <u>3.58</u>	-0.0 <u>-0.03</u>	0.74 <u>0.81</u>	116 <u>147</u>
Byrup Langsø	2410004542	0.365	9.5169	56.0213	8.56 <u>8.6</u>	60.9	6.0 <u>5.59</u>	8.26 <u>3.51</u>	0.94 <u>0.93</u>	0.89 <u>0.96</u>	49 <u>62</u>
Engelsholm Sø	2410005242	0.429	9.3209	55.7166	14.22	35.5	5.68 <u>6.26</u>	5.2 <u>5.65</u>	0.73 <u>0.71</u>	0.84 <u>0.74</u>	107 <u>139</u>
Esrum Sø	2410014592	17.37	12.3807	56.0363	14.1 <u>13.04</u>	62.4	7.74 <u>9.87</u>	4.22 <u>4.59</u>	0.88 <u>0.8</u>	0.94 <u>0.96</u>	96 <u>120</u>
Filsø (S)	2410011002	4.173	8.2075	55.7005	16.33 <u>15.88</u>	106.2	4.16 <u>4.2</u>	5.36 <u>4.31</u>	0.98	0.96	65 <u>84</u>
Flyndersø	2410026512	4.799	8.9603	56.5203	6.15 <u>7.92</u>	28.1	5.94 <u>6.28</u>	6.72 <u>6.3</u>	0.61 <u>0.62</u>	0.01 <u>0.46</u>	69 <u>88</u>
Furesø	2410014642	9.351	12.461	55.8105	15.6 <u>15.06</u>	29.3	4.61 <u>5.06</u>	7.98 <u>4.44</u>	0.69 <u>0.63</u>	0.58 <u>0.67</u>	96 <u>126</u>
Fårup Sø	2410010292	0.958	9.4176	55.7369	14.6 <u>12.88</u>	53.6	5.25 <u>5.02</u>	6.38 <u>5.04</u>	0.89	0.87 <u>0.89</u>	119 <u>149</u>
Grynderup Sø	2410026362	1.275	8.9517	56.7961	6.03 <u>6.41</u>	66.2	6.0 <u>5.87</u>	23.63 <u>3.91</u>	0.81	0.74 <u>0.95</u>	33 <u>42</u>
Gudensø	2410005972	1.682	9.7452	56.0618	12.35 <u>11.86</u>	38.6	4.29	4.8	10.33 <u>0.87</u>	0.86	0.55 <u>157</u>
Hinge Sø	2410024582	0.916	9.5287	56.2648	10.1 <u>10.53</u>	71.0	5.05 <u>5.36</u>	8.54 <u>5.15</u>	0.93 <u>0.92</u>	0.9 <u>0.92</u>	117 <u>148</u>
Jul sø	2130011152	8.451	9.6483	56.1202	13.75 <u>13.36</u>	47.8 <u>64.5</u>	4.23 <u>4.26</u>	51.27	0.91 <u>0.92</u>	0.42	132 <u>167</u>
Kimmerslev Sø	2410016382	0.377	11.9821	55.4862	9.79 <u>9.58</u>	85.5	6.46 <u>6.16</u>	90.33 <u>3.95</u>	0.94	0.67 <u>0.98</u>	80 <u>89</u>
Mossø †	2410005112	16.569	9.849	56.0482	15.69 <u>14.68</u>	74.2	5.31 <u>4.41</u>	5.19 <u>4.26</u>	0.96 <u>0.98</u>	0.97 <u>0.98</u>	133 <u>168</u>
None	2410011012	0.827	8.2234	56.1889	14.27 <u>14.72</u>	81.5 <u>84.9</u>	5.34 <u>5.79</u>	19.2 <u>5.57</u>	0.89	0.54 <u>0.85</u>	79 <u>97</u>
Ovesø	2410023522	3.725	8.4014	56.8889	17.28 <u>17.34</u>	167.5	5.36 <u>4.93</u>	5.03 <u>4.91</u>	0.99	0.99	68 <u>84</u>
Ravn sø	2410005102	1.791	9.8232	56.1038	12.56 <u>10.93</u>	84.6	4.7 <u>4.17</u>	5.46 <u>5.41</u>	0.97 <u>0.98</u>	0.97 <u>0.96</u>	126 <u>156</u>
Silkeborg Langsø (east)	2410005722	1.061	9.6003	56.1738	10.48 <u>9.78</u>	118.1 <u>124.9</u>	4.46 <u>4.06</u>	8.83 <u>4.72</u>	0.99	0.96 <u>0.98</u>	98 <u>125</u>
Skanderborg Sø	2410006032	8.646	9.9349	56.0341	13.59 <u>12.42</u>	93.2	5.69 <u>4.87</u>	5.94 <u>3.07</u>	0.97	0.96 <u>0.99</u>	101 <u>123</u>
Sliv sø	2410005352	1.688	9.46	55.1816	23.65 <u>23.29</u>	108.3	6.56 <u>6.16</u>	3.75 <u>6.1</u>	0.96	0.98 <u>0.95</u>	63 <u>79</u>
Stevning Dam	2410007182	0.288	9.3734	55.2385	17.33 <u>16.61</u>	63.3 <u>77.9</u>	10.49 <u>9.8</u>	3.06 <u>9.73</u>	0.61 <u>0.65</u>	0.96 <u>0.56</u>	73 <u>93</u>
Store Kattinge Sø	–	0.667	12.0244	55.6558	11.73 <u>11.45</u>	36.4 <u>40.2</u>	6.32 <u>5.87</u>	–	0.8 <u>0.81</u>	–	117 <u>138</u>
Stubbe Sø	2410024832	3.717	10.7223	56.2551	12.23 <u>12.54</u>	37.7	6.2 <u>6.15</u>	4.73 <u>4.29</u>	0.81	0.78 <u>0.87</u>	127 <u>154</u>
Søby Sø †	2410010372	0.709	9.0562	56.0483	7.47 <u>6.91</u>	16.8 <u>18.2</u>	5.13 <u>6.53</u>	4.11 <u>4.51</u>	0.4 <u>0.47</u>	0.3 <u>0.52</u>	118 <u>149</u>
Søndersø (Maribo)	–	8.075	11.4912	54.7569	17.18 <u>17.07</u>	71.9	6.12 <u>6.1</u>	–	0.93 <u>0.91</u>	–	61 <u>76</u>
Tange Sø	2410024672	5.428	9.5969	56.3111	10.91 <u>10.72</u>	40.6	3.92 <u>4.16</u>	5.78 <u>3.76</u>	0.84 <u>0.86</u>	0.55 <u>0.87</u>	132 <u>167</u>
Thorsø	2410005082	0.693	9.5576	56.1281	13.81 <u>13.24</u>	30.6	5.74	5.44	6.1 <u>0.49</u>	0.53 <u>0.64</u>	0.65 <u>117</u>
Tivolisøen †	2410015242	0.269	11.7442	55.4787	20.26 <u>19.06</u>	188.5 <u>188.6</u>	7.1 <u>6.82</u>	9.39 <u>6.53</u>	0.99	0.99 <u>0.98</u>	113 <u>132</u>
Tuel sø	2410015252	1.877	11.6014	55.4443	9.72 <u>9.64</u>	84.4	4.16 <u>4.18</u>	5.92 <u>4.2</u>	0.98	0.97 <u>0.98</u>	130 <u>160</u>
Valsølle Sø †	2410015112	0.703	11.8469	55.523	15.9 <u>15.47</u>	69.7	4.74 <u>4.89</u>	4.28 <u>5.33</u>	0.96 <u>0.95</u>	0.98 <u>0.9</u>	113 <u>137</u>
Vandet Sø	2410025112	4.783	8.5813	57.0058	14.09 <u>14.33</u>	74.9	4.37 <u>4.01</u>	3.54 <u>5.1</u>	0.98	0.97 <u>0.96</u>	69 <u>85</u>
Vandkraftsøen	2410025962	0.639	8.6389	56.3516	12.08 <u>12.18</u>	49.4	4.19 <u>4.16</u>	180.99 <u>3.41</u>	0.75	0.39 <u>0.83</u>	53 <u>70</u>
Vedsø	2410025832	1.497	9.4287	56.3996	7.13 <u>7.61</u>	20.6 <u>21.3</u>	4.56 <u>4.85</u>	11.93 <u>6.89</u>	0.55 <u>0.6</u>	0.15 <u>0.43</u>	120 <u>152</u>
Ørnsø	2410005052	0.404	9.5147	56.157	9.87 <u>9.65</u>	146.7	5.09 <u>5.57</u>	4.85 <u>4.66</u>	0.98	0.99	83 <u>104</u>
Ørum Sø	2410023442	4.447	8.2908	56.7931	20.32 <u>20.69</u>	103.5 <u>109.4</u>	4.97 <u>4.33</u>	5.31 <u>4.67</u>	0.97	0.95 <u>0.97</u>	69 <u>85</u>

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Competing interests. The authors declare that they have no conflict of interest.

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