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Open Access Earth System Science Data Discussions

GloLakes: a database of global lake water storage dynamics from 1984 to present derived using laser and radar altimetry and optical remote sensing

Jiawei Hou[1], Albert I.J.M. Van Dijk[1], Luigi J. Renzullo[1] and Pablo R. Larraondo[1]

[1]Fenner School of Environment & Society, Australian National University, Canberra, ACT, Australia

Correspondence to: Jiawei Hou (jiawei.hou@anu.edu.au)

Abstract. Measurements of the spatiotemporal dynamics of lake and reservoir water storage are fundamental in the assessment of the influence of climate variability and anthropogenic activities on water quantity and quality, as well as wetland ecology and the estimating greenhouse gas emissions from lakes. Previous studies estimated relative water volume changes for lakes where both satellite-derived extent and radar altimetry data are available. This approach is limited to only few hundreds of lakes worldwide. In this study, the number of measured lakes was increased by a factor 400 using high-resolution Landsat and Sentinel-2 optical remote sensing and ICESat-2 laser altimetry in addition to radar altimetry from the Topex/Poseidon, Jason-1, -2 and -3, and Sentinel-3 instruments. Time series of relative (i.e., storage change) or absolute (i.e., total stored volume) storage for more than 170,000 lakes globally with a surface area of at least 1 km^2 (representing 99% of the total volume of all water stored in lakes and reservoirs globally) were retrieved. Within these, we were able to develop an automated workflow for near real-time global lake monitoring of more than 27,000 lakes. The historical and near real-time lake storage dynamics data for 1984 to current are publicly available through https://doi.org/10.25914/K8ZF-6G46 (Hou et al., 2022).

1. Introduction

Lakes and reservoirs are a key component of the global water cycle through their contribution to land-atmosphere, river-floodplain, and groundwater systems. Lakes also emit substantial quantities of carbon dioxide and methane to the atmosphere through biogeochemical processes (Bastviken et al., 2011; Raymond et al., 2013). The seasonality of natural lakes sustains ecosystems and biodiversity, whereas constructed reservoirs provide an often essential water supply to society (Vörösmarty et al., 2010). Therefore, monitoring the quantity and quality of these surface water stores has important implications across a wide range of societal, environmental and economic areas.

Globally it has been observed that surface water resources have become vulnerable to climate change and anthropogenic pressure (Vorosmarty et al., 2000). The processes, influences and consequences involved are still poorly understood, in the absence of long-term historical spatiotemporal dynamic information for lake dynamics. Shifts in seasonal cycles and extreme

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events are reported or predicted for many lakes due to climate change, which may worsen the already uneven distribution of water resources (Oki and Kanae, 2006; Wang et al., 2018). This stresses the need for global monitoring of lake dynamics, preferably in near real-time (NRT), e.g., a latency of 1~10 days.

Remote sensing approaches to global lake monitoring has benefitted from the substantial increase of Earth observation technologies over the last four decades (Papa et al., 2022). The remote sense technologies and techniques offer a monitoring capability with a coverage and consistency that is impossible to achieve with in situ networks (Alsdorf et al., 2007). For example, the large majority of lakes are ungauged, perhaps because they are generally more significant to ecosystems and for biodiversity than for human activities and economic gain. Many large reservoirs, as capital investment constructions, are gauged well but these records are generally not publicly accessible. All these issues impede understanding the change and variability of lakes worldwide. Therefore, remote sensing provides the best monitoring tool to tackle these issues and improve our incomplete knowledge about long-term changes in lakes at the local, regional and global scale.

Accurately locating lakes and reservoirs is the first step towards monitoring storage dynamics with remote sensing. Lehner and Döll (2004) used a wide range of available data and digital maps to develop the Global Lakes and Wetlands Database (GLWD), which delineated the boundaries of global lakes and reservoirs with a combined area of 2.7 million km^2. Based on GLWD and other regional and global data sources, Messager et al. (2016) developed the HydroLAKES database that provides detailed attribute information, such as shoreline length, size, and hydraulic residence times for 1.43 million lakes. The Global Water Bodies Database (GLOWABO) developed by Verpoorter et al. (2014) detected around 117 million lakes based on high-resolution satellite imagery. However, this dataset does not distinguish between lakes, rivers, floodplains and wetlands, unlike the HydroLAKES database, which means that the reported number of lakes is an overestimate. Lehner et al. (2011) complied the storage capacity and characteristics of 6,862 dams and reservoirs in the Global Reservoir and Dam database (GRanD). By 2020, there were 58,713 dams registered in the International Commission on Large Dams (ICOLD), but most of them are still not georeferenced. This gap was addressed by the Global Georefenced Database of Dams (GOODD), in which Mulligan et al. (2020) captured the locations of more than 38,000 dams from multiple satellite sources.

Radar altimetry, such as from the TOPEX/Poseidon, Jason-1/2/3, ENVISAT, ERS-1/2 and Sentinel-3 instrument, has proven useful to measure water levels in lakes and reservoirs (Birkett, 1998; Da Silva et al., 2010; Frappart et al., 2006). Global time series of radar altimetry-derived surface water elevation have been compiled in several places, including Hydroweb (Crétaux et al., 2011), the Database for Hydrological Time Series of Inland Waters (DAHITI) (Schwatke et al., 2015), and the Global Reservoirs and Lakes Monitor (G-REALM) (Birkett et al., 2010). Based on the G-REALM dataset, Kraemer et al. (2020) evaluated long-term trends in the water level of lakes globally, but this study was limited to around 200 lakes for which radar altimetry data was available. In contrast, Cooley et al., (2021) demonstrated the ability of ICESat-2 laser altimetry to measure water level variability for a larger number of lakes globally. The spatial resolution of global satellite-derived surface

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water dynamics products has been improved significantly over the last two decades. Prigent et al. (2007) and Papa et al. (2010) developed a monthly and 25-km resolution surface water extent dataset based on a combination of passive (Special Sensor Microwave/Imager (SSM/I)) and active (European Remote Sensing (ERS)) microwave and optical remote sensing (Advanced Very High Resolution Radiometer (AVHRR)). This was improved to daily and 250 or 500-m resolution in the surface water dataset developed by Ji et al. (2018) and in the Global WaterPack (Klein et al., 2017). The 30-m resolution surface water maps developed by Pekel et al. (2016) from imagery from the Landsat satellite series has been one of the most promising data sources to help understand long-term changes in surface water resources on Earth. Landsat archives have been the most popular data to investigate long-term changes and variability in lakes and reservoirs at either global or regional scale, benefiting from the four decades-long archive of images with global coverage and 30-m high resolution, (Ogilvie et al., 2018; Sheng et al., 2016; Tao et al., 2015; Yao et al., 2019; Zhao and Gao, 2018).

Surface water height and extent are the two basic components to measure water storage change in lakes and reservoirs. The daily or 8-day composite MODIS AQUA/TERRA products are less affected by cloud cover than 16-day Landsat observations, and new MODIS images are updated with sufficient timeliness to support NRT water monitoring. Some studies have used MODIS-derived water extents and altimetry data to estimate lake storage changes, such as the Mackenzie Delta or South Asia, or worldwide (Gao et al., 2012; Normandin et al., 2018; Tortini et al., 2020; Zhang et al., 2014). However, the 500-m spatial resolution of MODIS fail to detect changes in a large majority of smaller lakes, of which the number soars exponentially as the lake size deceases. The 30-m resolution Landsat data, in combination with different altimetry sources, have been shown a better option to estimate water volume dynamics in lakes and reservoirs, especially those with relatively slowly changing extent (Busker et al., 2019; Duan and Bastiaanssen, 2013). Landsat satellite series can provide historical observations back to 1980s. Finally, while MODIS- or Landsat-derived water extent and altimetry data have demonstrated capability to estimate changes in lake water storage, they cannot measure lake depth and therefore absolute water storage volume without the use of bathymetric data. Avisse et al. (2017) proposed an approach to estimate absolute water volume based on an analysis of DEMs for reservoirs that were not yet constructed or empty at the time of DEM capture. Messager et al. (2016) used the surrounding terrain data (i.e., slope derived from the DEM) while Khazaei et al. (2022) used geophysical characteristics and hypothetical idealised geometry (i.e., cone, box, triangular prism, and ellipsoid) to estimate water depth for lakes in the absence of bathymetry. However, there are currently no such data products that provide absolute lake volume dynamics at global scale.

This study aimed to produce both relative and absolute water storage dynamics for lake worldwide. Our dataset not only provides nearly four-decades of volume measurements but also enables a global, NRT lake monitoring capability. The methods to estimate lake storage in the previous studies were limited to a few hundred lakes that lie beneath the sparse ground tracks of radar altimetry instruments. With its much denser coverage, we found that ICESat-2 laser altimetry data could increase the number of measurable lakes by a factor of 400. Furthermore, we estimated water body extents between

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1984-2020 from Landsat-derived surface water maps for 170,957 lakes. Relative storage changes were then estimated based on Landsat-derived extents and radar and laser altimetry data while absolute storage dynamics were calculated using a geostatistical model (Messager et al., 2016). This was possible for more than 27,000 lakes and reservoirs worldwide. NRT monitoring was achieved by implementing radar and laser altimetry data into a hypsometric relationship. In addition, Sentinel-2 derived lake water extent were used to complement the Landsat estimates to further increase the monitoring capability. The core strategy to develop this global lake monitoring system is to consider different kinds of freely accessible, validated, and updated satellite data, and to explore the advantage of each satellite source and complement their respective weaknesses.

2. Data and method

2.1 Data

2.1.1 Surface water extent

The Joint Research Centre's Global Surface Water Dataset (GSWD) provides the spatial and temporal distribution of surface water and their statistics at global scale over the last 37 years. Open water areas larger than ca. 30 m × 30 m were detected by an expert system using Landsat-5 Thematic Mapper (TM), Landsat-7 Enhanced Thematic Mapper-plus (ETM+) and Landsat-8 Operational Land Imager (OLI) images between 1984 and 2020 (Pekel et al., 2016). The omission errors of water mapping from Landsat-5, -7 and -8 are less than 5%, while the commission errors are less than 1%. Monthly water history and monthly recurrence products from GSWD are used in this study. The monthly water history product provides monthly water mapping from March 1984 to December 2020 and each pixel was classified as open water, land, and non-valid observation. The monthly recurrence product comprises 12 datasets for each month (from January to December). Each dataset shows the frequency of inundation in each pixel as a percentage of the number of time water is detected over the total number of clear observations in the full-time series. The BLUEDOT water observatory (https://www.blue-dot-observatory.com/aboutwaterobservatory) provides 5-day near real-time (NRT) measurements of surface water extent from 2015 to present for 8,837 lakes globally. The surface water map is derived using normalized difference water index (NDWI) from clear-day optical Sentinel-2 imagery. We used these data to complement our Landsat data.

2.1.2 Surface water height

The Advanced Topographic Laser Altimeter System (ATLAS) onboard the Ice, Cloud and land Elevation Satellite-2 (ICESat-2) launched by NASA in 2018 is designed to measure the elevation of ice sheets, oceans, lakes and vegetation with a 91-day repeat cycle. ATLAS/ICESat-2 determines elevation by measuring the return time of a laser pulse between the satellite and the Earth surface. The six laser beams from ICESat-2 allows it to cover more ground coverage of the Earth's surface, compared to its predecessor (ICESat-1). ATLAS/ICESat-2 L3A along-track inland surface water data (version 5) was used in this study (Jasinski and Ondrusek, 2021). It provides surface water height measurements for inland water bodies

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including rivers, lakes, reservoirs and coastal water from 2018 to present. They reported an error per 100 inland water of 6.1 cm (Jasinski and Ondrusek, 2021). The mean absolute error between USGS gauge data and ICESat-2 height measurements is 0.14 m (Cooley et al., 2021).

The Global Reservoirs and Lakes Monitor (G-REALM) provides NRT surface water height dynamics for 392 lakes globally using a combination of different satellite radar altimetry (Birkett et al., 2010). It has two on-going products: one is the 10-day NRT water heights from 1993-present using Topex/Poseidon and Jason 1/2/3, and the other is the 27-day NRT water heights from 2016-present using Sentinel-3A. Satellite radar altimetry determines the surface height by emitting microwave pulses towards the Earth's surface and measuring the travel time between pulse emission and echo reception. The accuracy of these radar altimetry-derived water heights varies, mainly depending on the roughness and extent of the water body, but is typically a few cm.

2.1.3 Geo-statistical model

The HydroLAKES database provides the boundary outlines of more than 1.4 million individual lakes globally with a surface area above 0.1 km^2 (Messager et al., 2016). This database is compiled from several global and regional lake and reservoir datasets derived using topographic maps, optical remote sensing imagery composites and radar instruments. HydroLAKES also comprises a geo-statistical model with parameters to predict average water depths and volumes based on surrounding topography information for lakes with a surface extent between 0.1 km^2 and 500 km^2. The symmetric mean absolute percent error (see Eq.2 below) between predicted and reference volume is 48.8% and there is no significant bias in volumes for the majority of lakes around the world with the exception of Finland, Sweden and northwestern Russia, European Alps, and the Andes (Messager et al., 2016). The HydroBASINS database delineates watershed boundaries worldwide at different basin or catchments scales (Lehner and Grill, 2013). The catchment boundaries in the Pfafstetter level-3 product from HydroBASINS were used as the basic units for lake statistical analysis in this study.

2.2 Method

2.2.1 Global historical lake volume estimation

We estimated water surface extent of future GSWD water bodies, where the shoreline polygons of lakes or reservoirs were delineated with HydroLAKES as follows. First, we overlaid each lake boundary polygon from HydroLAKES on top of GSWD. Second, we introduced a 500-m buffer around the lake to estimate maximum water extent or possible lake expansion due to hydrological variability. Third, for each lake, we calculated the number of wet pixels within the lake boundary polygon from the GSWD monthly water history product from 1984 to 2020. Lake water extent was then estimated by multiplying the total number of wet pixels by the grid pixel area. During this process, we also calculated the contamination ratio of each image as the ratio of non-valid pixel values over all pixel values within the lake boundaries. Water extent was

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not estimated for lakes smaller than 1 km^2 due to the limited spatial resolution of Landsat. Finally, monthly lake water extent time series were produced for 170,957 lakes world-wide.

Landsat images are affected by suboptimal observation conditions (e.g., cloud and cloud shadows) and data acquisition (e.g., swath edges, the Landsat-7 Scan Line Corrector failure) and limited archiving of acquired imagery. This then reduces the total number of effective Landsat image available over 37 years to derive water extent dynamics for many lakes. Many studies chose to either use images with a contamination ratio below a certain threshold (e.g., 5%) or to aggregate the 16-day or less temporal resolution to seasonal, annual or five-year averages (e.g., Shugar et al., 2020; Yang et al., 2020). However, low frequency time series can miss important monthly, seasonal and interannual changes in surface water extent. Alternatively, higher temporal frequency satellite data such as MODIS may be used to fill gaps in the Landsat imagery (e.g., Li et al., 2021). However, this is only possible for the MODIS era, i.e., after 2000, and the spatial resolution of MODIS poses an additional constraint on the size of the lake that can be monitored.

Here, we applied a simple and effective gap-filling approach (Hou et al., 2022) to recovery missing data in partial Landsat water mapping to boost the total number of usable images. Unlike Hou et al. (2022), this study used corresponding monthly recurrence map, rather than a multi-year average recurrence map, to restore the contaminated water map for the specific month considered, which makes it sensitive to seasonal changes as much as possible. In summary, the monthly GSWD recurrence product was used to address missing data in any given month (January to December), considering the seasonal changes in surface water extent. For example, the contaminated surface water map derived from Landsat in January 2022 was restored by the January recurrence data. This is achieved by, first, for each contaminated image, matching the GSWD extent mapping for different recurrence frequencies in the corresponding month to the available parts of the image. The differential evolution method (Storn and Price, 1997) was used to find the best-fit frequency, i.e., minimising the difference between the recurrence mapping and monthly water mapping. Subsequently, the mapping at the best-fit recurrence frequency was used to reconstruct missing data. The algorithm was implemented for all images with contamination ratios ranging from 5% up to 70%. The efficacy of this approach was evaluated and confirmed in a previous publication (Hou et al., 2022).

For each lake, mean lake water depth dynamics were calculated based on the estimated water extent time series using a geo-statistical model. This model provides empirical equations relating water depth with water extent and slope within a 100 m buffer around the lake for difference size of lakes (Messager et al., 2016). The basic principle is that we can extrapolate mean lake water depth from local slopes of surrounding topography. The predicted mean water depths were bias-corrected by the residual variance of its corresponding empirical equations (Messager et al., 2016). Lake water volumes were estimated by the bias-corrected predicted water depths multiplied by water extents. Ultimately, we produced monthly water storage dynamics from 1984-2020 for 170,611 lakes globally.

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2.2.2 Global near real-time lake volume estimation

To provide routine and low-latency measurements of lake water storage, we obtained NRT satellite-derived water heights and extents from different monitoring platforms, including the National Snow & Ice Data Center (NSIDC), U.S. Department of Agriculture (USDA) and BLUEDOT water observatory (Table 1). We selected all measurements for lakes whose volume dynamics from 1984–2020 were derived from GSWD with the geo-statistical model. As there are overlapping monthly time series between historical volume (V) and NRT height (H) or area (A), we can use their pairwise relationship (i.e., V-H or V-A) to extend historical volume estimation to NRT monitoring using only satellite-derived H or A. We only applied this method when there was a statistically significantly ($p<0.05$) correlation between the predictor and predictand. Specifically, we calculated the significant Pearson correlation threshold (R_t) using a t-test allowing for sample size N (i.e., the number of data pairs). If the Pearson correlation (R) between V-H or V-A exceeded R_t we used H or A, respectively, to estimate lake storage dynamics after 2021. As the relationship is necessarily monotonic, lake storage was estimated using cumulative distribution function (CDF) matching. In practice, a look-up table was developed to rank all historical A or H and V, allowing one to be estimated from the other based simply on the ranking. In total, we produced historical and NRT water storage dynamics from 1984 onwards for 23,294 lakes using ICESat-2, 67 lakes using G-REALM, and 4,054 lakes using Sentinel-2.

Table 1 Sources of satellite data for lake water monitoring that have observations overlapping with the Landsat-derived water extent dataset.

Dataset	I	II	III
Platform	NSIDC	USDA	BLUEDOT
Source	ICESat-2	G-REALM (several satellites)	Sentinel-2
Period	2018-current	1993-current/2016-current	2015-current
Type	laser altimetry	radar altimetry	optical
Variable	height	height	extent
Temporal resolution	91 days	10-days/27-days	5-days
Overlapping with Landsat (number)	101,983	255	5,948
Successfully constructed in this study (number)	25,495	168	4,102

In addition to these absolute lake volume storage estimates, we produced relative storage estimates where both radar or laser-derived surface water heights as well as Landsat-derived surface water extents were available. We calculated storage changes for lakes where the A-H relationship was significant correlated as follows (Crétaux et al., 2016):

$$\Delta V = \frac{(H_t - H_{t-1}) \times (A_t + A_{t-1} + \sqrt{A_t \times A_{t-1}})}{3} \quad (1)$$

where ΔV is storage change between two consecutive measurements; H_t and H_{t-1} are radar or laser altimetry derived surface water heights at time t and t-1, respectively; A_t and A_{t-1} are optical remote sensing derived surface water extents at time t and

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t-1, respectively. Where there are only H data available after 2021, we estimated corresponding A using CDF matching. Overall, we estimated relative lake storage dynamics from 2018 onwards for 23,419 lakes using ICESat-2 and Landsat, and from 1993 onwards for 148 lakes using G-REALM and Landsat.

3. Results and Discussion

3.1 Improved lake extent mapping after image gap-filling

A large portion of Landsat data were missing due to cloud, cloud shadow and the Landsat-7 Scan Line Corrector (SLC) failure. Unmitigated, this issue would have resulted in the limited number of observations per year or underestimation of surface water area even if using an image with a low contamination ratio. Cloud cover is the most common issue, but water extent could be reconstructed for contamination ratios of 58% and higher (Figs. 1 and 2). The SLC failure resulted in missing data of around 22% after 2003 (Chen et al., 2011) . Missing data could also be caused by a combination of cloud cover, SLC failure and swath edges, for example (Figs. 1 and 2). The reconstructed water extent maps in the rightmost column of Figs. 1 and 2 demonstrate that these missing data scenarios could be usefully restored. By applying this step, we much increased the number of effectively useful images.

3.2 Coverage

We were able to estimate monthly lake volume dynamics for 170,611 lakes for the period 1984–2020 (Fig. 3a). Most of them are distributed across the northern hemisphere high latitude regions, especially in northern North America. The GloLakes dataset also provides near real-time volume estimates for 27,599 lakes. We considered all lakes with an area greater than 1 km^2 given the limitations of the Landsat imagery. There are more than a million lakes with areas between 0.1–1 km^2 that remain unmeasured, but combined storage of these small lakes only account for 1% of global total lake water storage, according to HydroLAKES. Overall, the vast majority of global lake volume has been measured in this study (Fig. 3b and c). Over three-fourths of total lake basin volume have been measured either by optical remote sensing (i.e., extent) or altimetry (i.e., height) in 200 basins (79% of the total number of lake basins) (Fig. 3b). Over the half of total basin lake and reservoir volumes was estimated in 209 basins (83%) around the world, but coverage was poorer for several basins in tropical regions of Africa and the northern high latitude regions (Fig. 3c). The poor coverage in some basins is due to either the overlapped periods between extent and height observations is not long enough to perform as training data or the volume is more sensitive to height variability rather than the nearly constant extent (resulting in a weak A-H relationship).

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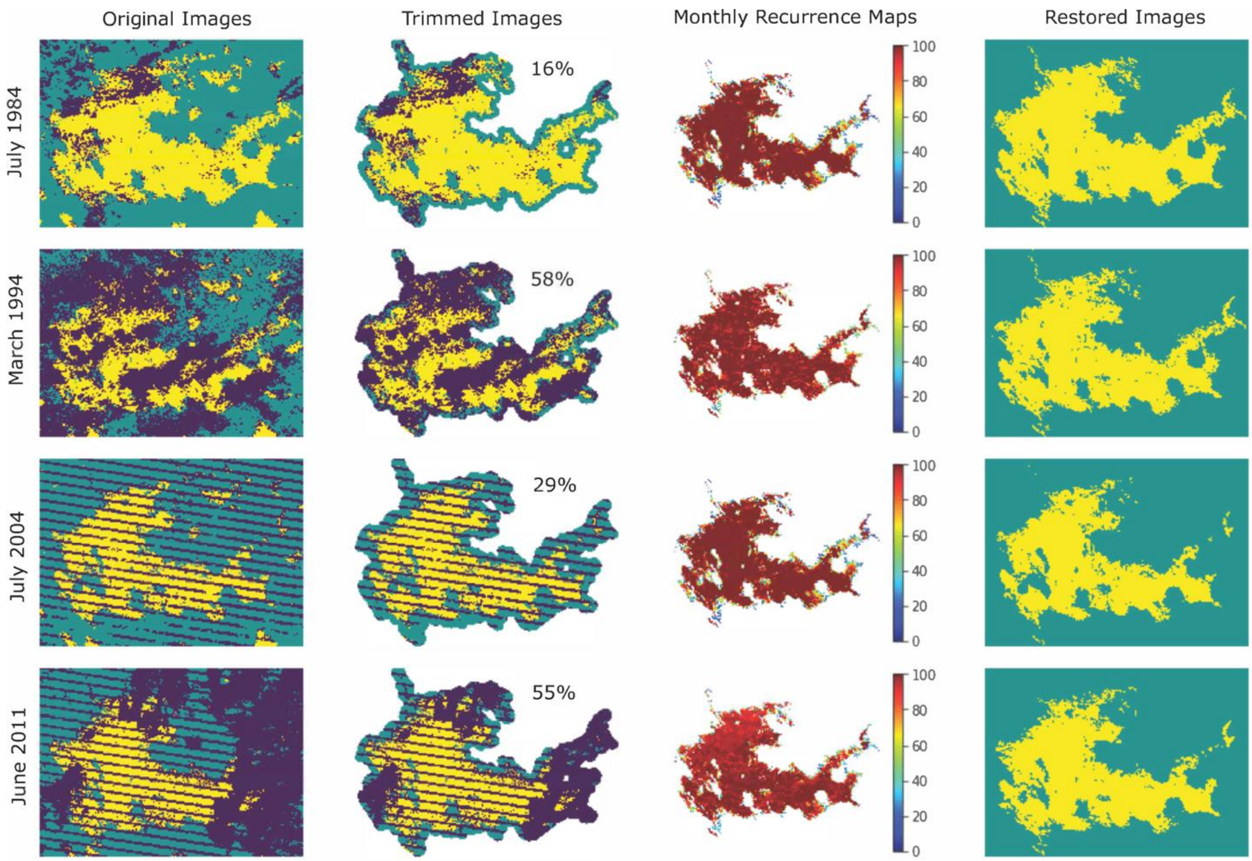

245 **Figure 1.** Examples of the performance of the image gap-filling algorithm in Lake Rossignol, Canada. (First column: historical water maps from GSWD (yellow: water; green: land; blue: no data; image contaminated ratio from top to bottom: 16%, 58%, 29% and 55%); second column: historical water maps trimmed by the lake boundary from HydroLAKES with a 500 m buffer (number: contamination ratio); third column: water recurrence (0~100%) maps at the specific month; fourth column: restored water maps)

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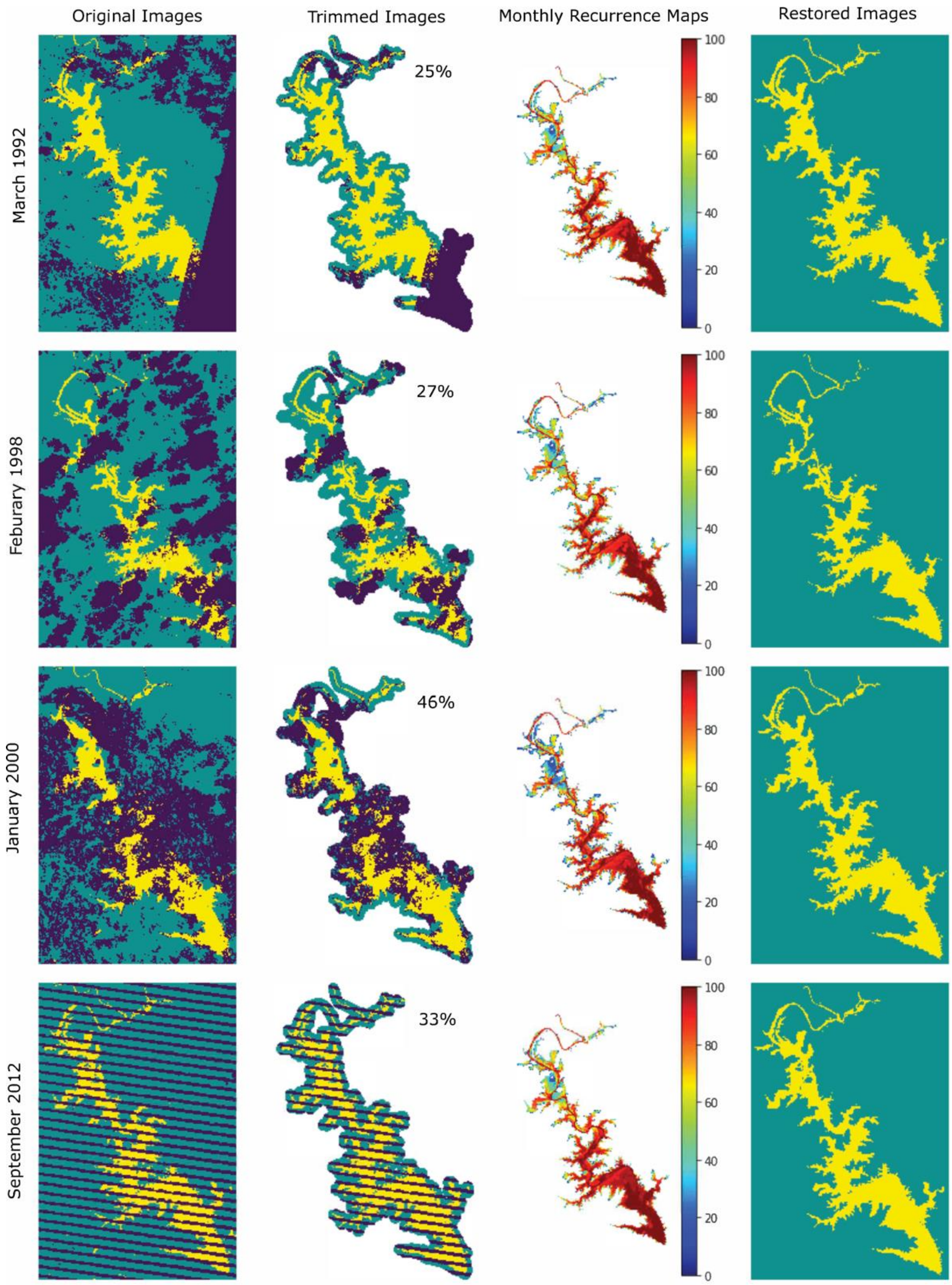

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Figure 2 As in Fig. 1 but for Lake Wivenhoe, Australia. (First column: historical water maps from GSWD (yellow: water; green: land; blue: no data image contaminated ratio from top to bottom: 25%, 27%, 46 % and 33%); second column: historical water maps trimmed by the lake boundary from HydroLAKES with a 500 m buffer (number: contamination ratio); third column: water recurrence (0~100%) maps at the specific month; fourth column: restored water maps)

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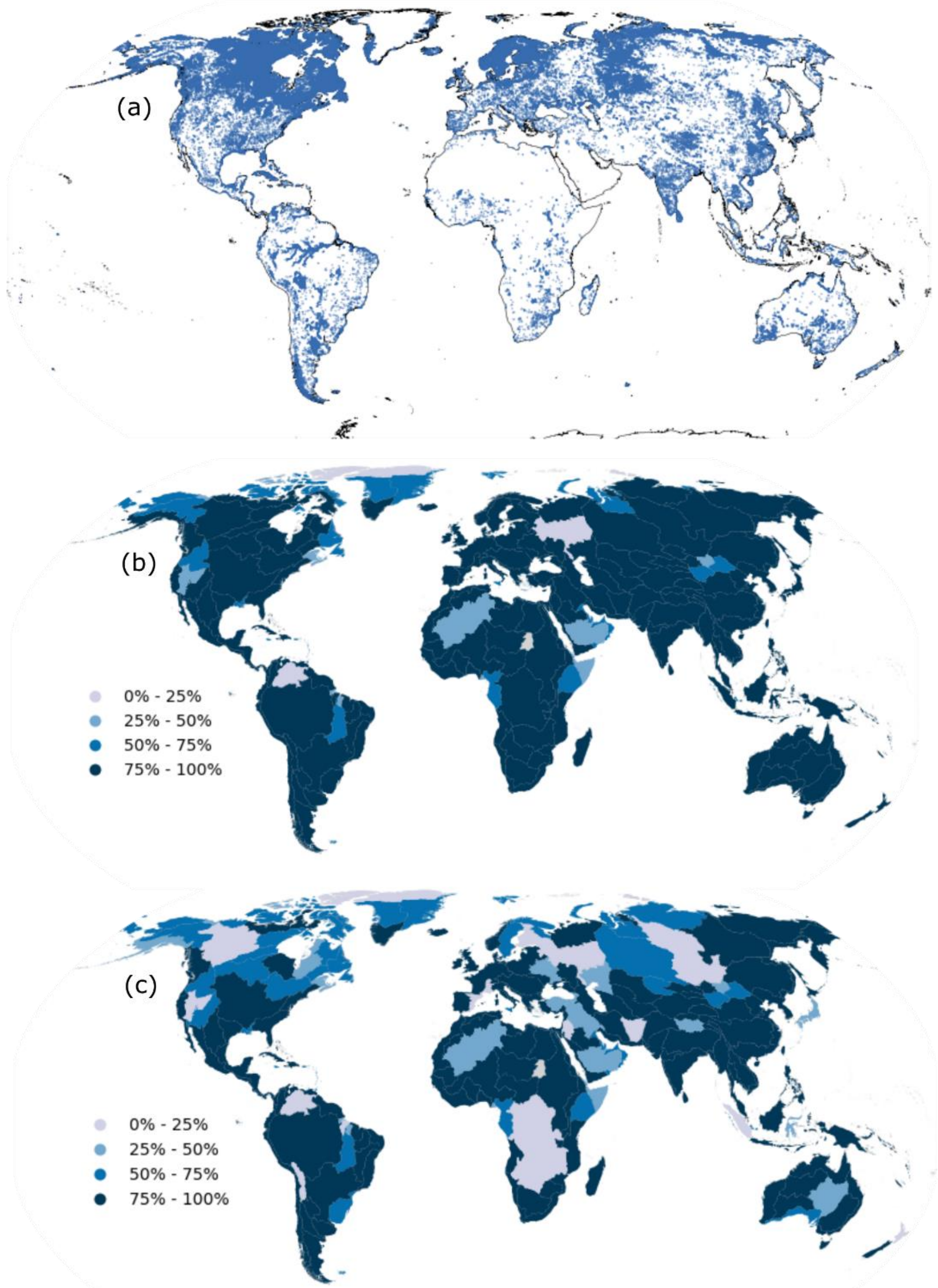

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Figure 3 a) The locations of 170,957 lakes whose storage dynamics for the period of 1984-2020 were measured in this study, b) the ratio (%) of measured extent or/and height (covert to volume) in this study and total volume recorded in HydroLAKES, and c) the ratio (%) of measured volume in this study and total volume recorded in HydroLAKES in each of 253 basins worldwide.

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3.3 Validation

There is a general lack of independent and publicly available lake and reservoir storage data with which to validate our results. Nonetheless, we were able to validate lake volume time series estimates against in situ measurements for 238 lakes in Australia and the USA available from the Australian Bureau of Meteorology and United States Bureau of Reclamation, respectively. We evaluated the accuracy of lake volume time series by Pearson correlation (R) and the symmetric mean absolute percent error :

$$SMAPE = 100 \times \frac{1}{N}\sum\frac{|observed\ volume - predicted\ volume|}{(observed\ volume + predicted\ volume)/2} \qquad (2)$$

The results suggest an average R between reported lake volumes and our estimates of 0.78 and a SMAPE of 52.5%. This SMAPE is similar to that reported in Messager et al. (2016) (48.8%). Selected lake volume comparisons are shown in Fig.4, chosen to represent different size of lakes. For many applications, the relative agreement (e.g., R) may be more relevant than the absolute error, as the latter can be affected by several factors. For example, the delineation of lake shorelines from HydroLAKES can be different than those used for in situ measurement, as the spatial definition to distinguish the lake from connected rivers or wetlands can in practice be ambiguous. As a result, predicted volumes are not directly comparable to in situ data and there can be systematic over- or underestimation. Secondly, lake volume cannot be estimated very precisely unless detailed lake bathymetry data is available, but this is beyond current satellite remote sensing abilities. We used a geo-statistical model to estimate lake depth. The estimation accuracy largely depends on the quality of the DEM used and the degree to which the relationship between the topography of the lakebed and the slopes surrounding the lake is such that the underlying assumptions are supported. Overall, the relative volume dynamics are generally more reliable, as demonstrated by the correlation values. Nonetheless, the estimated volumes are within 10% of reported values for many lakes and reservoirs.

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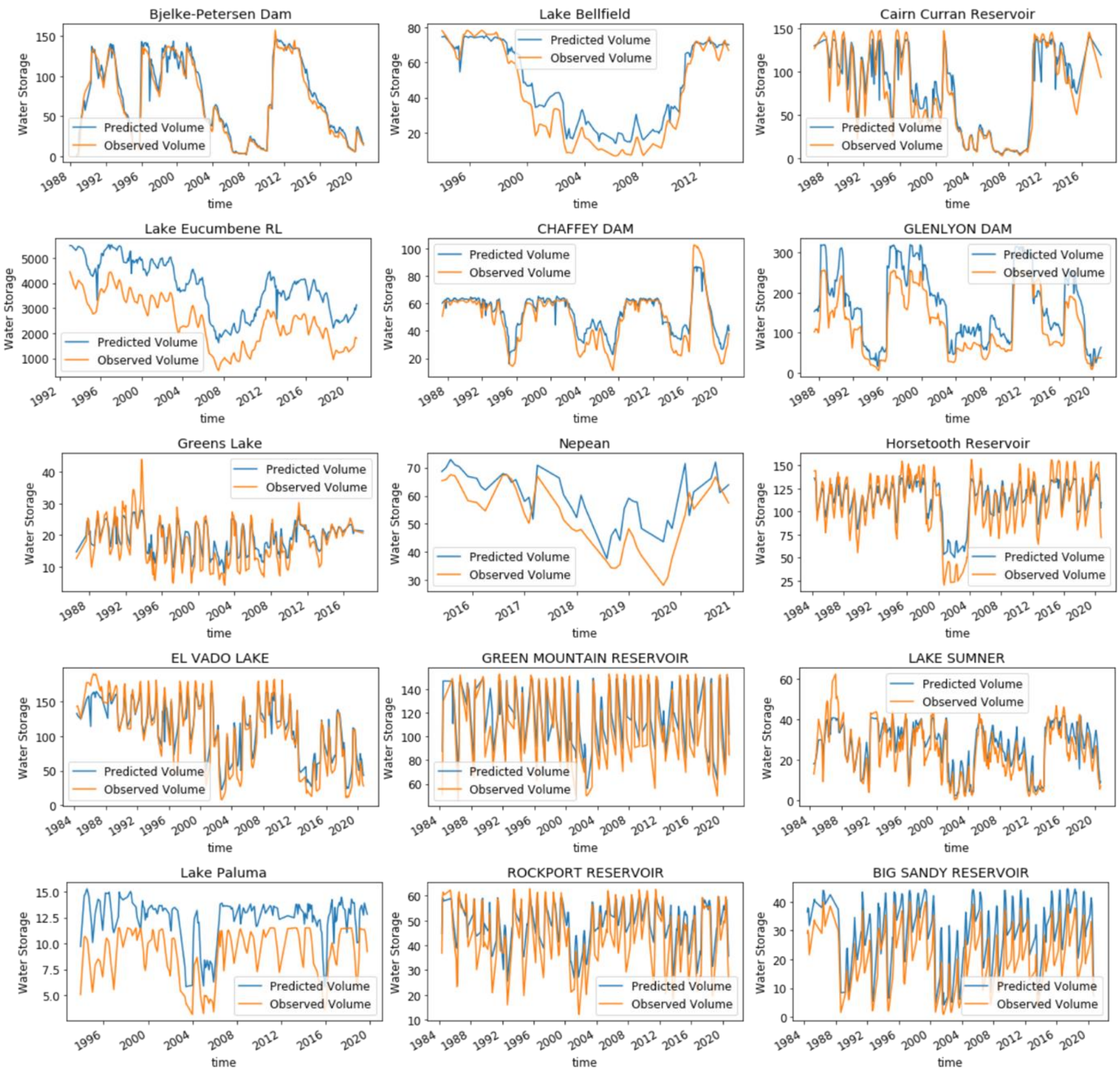

Figure 4 Some comparisons of predicted lake water storage from GloLakes against in situ (observed) data..

3.4 Comparison with other datasets

We compared our monthly lake area time series estimates with the Global Reservoir Surface Area Dataset (GRSAD) v2 (Zhao and Gao, 2018). GRSAD provides monthly reservoir surface area time series estimates from 1984–2018 based on the Landsat-derived GSWD (Pekel et al., 2016), with image contamination issues corrected as well, but using a different method. For 5,323 overlapping water extent time series pairs, we found strong agreement between GRSAD and our product, with average R of 0.88 and SMAPE of 3.6%. Among them, the correlation for data derived from Landsat images with minor

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contamination issues (i.e., missing data <5%) reached 0.97. The difference between these two products is mainly due to the different approaches to gap-filling contaminated images. The image gap-filling algorithm developed by Hou et al. (2022) and applied in this study is more easily implemented in rapid NRT image processing, however.

To our knowledge, we produced the first four decades-long relative and absolute lake storage dynamics for all HydroLAKES registered lakes with area exceeding 1 km^2. Previous studies have mainly focused on measuring relative lake storage dynamics using remote sensing. For example, Busker et al. (2019) used Landsat imagery and radar altimetry to estimate lake volume variations for 137 lakes, and Tortini et al. (2020) produced a storage change dataset for 347 lakes in a similar way but using MODIS instead of Landsat imagery. Furthermore, none of these studies tested a NRT monitoring capacity. They were also limited to a few hundred of lakes due to the sparse track of radar altimetry. With denser coverage, the ICESat-2 laser altimetry improves the number of measured lakes by a factor of more than hundred. Based on this, we were able to measure a wide range of lakes at global scale. Busker et al. (2019) did not make their lake dataset publicly accessible but the data produced by Tortini et al. (2020) can be downloaded from the Physical Oceanography Distributed Active Archive Center (PODAAC) of NASA's Jet Propulsion Laboratory. We compared our relative lake storage dynamics dataset against their global surface water storage change time series for 1992–2018 for 104 common lakes. The result showed that the two datasets have a strong agreement, with average R of 0.90.

It is not possible to remotely sense bathymetry for the great majority of lakes and reservoirs, and indeed even in situ surveys can be challenging and error-prone due to a limited number of sometimes imprecise measurements across the lake. According to the validation results in Section 3.3, the SMAPE error of our absolute lake storage dataset is around 52.5%, in the order as Messager et al. (2016). The geo-statistical model extrapolated lake bathymetry from the surrounding topography. Thus, its accuracy largely depended on the errors from the digital elevation models and can vary in different landscapes depending on relief and any change from above- to below-water topography. Khazaei et al. (2022) used HydroLAKES-derived surface area, elevation, volume, shoreline length, and watershed area to estimate maximum lake depth, and applied a distance method (Hollister and Milstead, 2010) to develop a lake bathymetry map by converting Euclidean distance to shoreline into depth based on the estimated maximum depth. Doing so they produced the GLOBathy dataset, which provides the height-area-volume (h-A-V) relationship for each lake delineated by HydroLAKES. We used these h-A-V relationships as an alternative to the geo-statistical method, and estimated absolute lake storage dynamics from 1984 onwards and validated the resulting alternative product against in situ lake storage records. The SMAPE error resulting from the GLOBahty method is 70.5%, which is greater than that from the geo-statistical method. This led our choice to use the geo-statistical method in favour of the GLOBathy dataset in this study.

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3.5 Future opportunities to monitor lake storage changes

Remote sensing can measure the majority lakes worldwide and provide NRT information, which is not possible with the current in situ network. Both Topex/Poseidon (1992-2002) and Jason 1/2/3 (2002-present) are able to measure lake height every 10 days, which can be adequate to trace the variability of lakes. The ability to monitor lake heights at 10-day temporal resolution will be continued by Sentinel-6 (a.k.a. Jason-CS) launched in 2020. However, many smaller lakes located in between the sparse ground-tracks cannot be detected by these radar altimeters. The ICESat-2 laser altimeter can cover a much larger number of lakes globally, benefiting from its dense reference tracks that are further enhanced by the six laser beams onboard. The trade-off is that its temporal resolution is only 91 days, but this is still sufficient to observe seasonal changes in lakes, and more frequent water extent mapping can be used to interpolate between these observations. The Landsat-derived GSWD was used to estimate lake surface water extents from 1984-2020 in this study. The GSWD will be updated annually by the Joint Research Centre of the European Commission (https://global-surface-water.appspot.com/download), meaning lake extent estimates can be extended beyond 2020. Although Landsat is not able to provide NRT observations, this weakness can be addressed using MODIS and Sentinel-2, for example. The daily or 8-day composite MODIS products have a better chance to provide valid observations than the 16-day Landsat images, but the 250-m or 500-m resolution is often not sufficient to detect lake area changes accurately. Five-day, 10-m resolution surface water extent data derived from Sentinel-2 would be a promising product for global lake monitoring, but presents some challenges for storage and easy access. The main limitation of using any optical remote sensing is the effect of cloud and, to a lesser extent, vegetation. This issue can be mitigated by using passive microwave sensors or SARs. The Japanese Space Agency's AMSR2 and TRMM TMI sensors and NASA's AMSR-E and GPM instruments can provide daily observations of surface water based on different in brightness temperature between wet and dry areas (De Groeve et al., 2015; Hou et al., 2018). Unfortunately, their resolution is generally very coarse due to the observation method. Sentinel-1 SAR could be a more practical solution to monitor lakes under cloud cover, with 2–12 days and 10-m resolution, provided the water detection algorithm can be automated and vegetation cover does not interfere with the mapping. The Surface Water and Ocean Topography (SWOT) satellite mission will be launched at the end of 2022, which will measure surface water height and extent simultaneously every 21 days for lakes greater than 250 m by 250 m. Its temporal resolution sits between radar and laser altimetry used in this study. The spatial resolution is lower than Landsat and Sentinel-2, but SWOT shows promise for monitoring lake changes given the two basic components (i.e., A and H) needed to estimate lake volume change are measured at the same time.

4. Data availability

The global historical and near real-time lake storage data described here are available from https://dx.doi.org/10.25914/K8ZF-6G46 (Hou et al., 2022). Five products are provided, the details of which are listed in Table 2. The products can be linked to the HydroLAKES database using the ID index provided in the metadata. This allows

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users to combine storage dynamics data with other lake attributes, such as latitude, longitude, lake type, shoreline length, hydraulic residence times, watershed area, etc. Using the same HydroLAKES metadata, our dataset can be coupled to the GRanD (Lehner et al., 2011), HydroSHEDS (Lehner et al., 2008), and HydroRIVERS (Lehner and Grill, 2013) data bases. Thus, users can access additional river and reservoir information and implement the data in hydrological model configuration, e.g., to improve river routing. The global lake dynamics are also accessible and visualised through the Global Water Monitor (the experimental version: http://wenfo.org/global-water/staging/), which along with NRT information on, among others, river discharge (Hou et al., 2020; Hou et al., 2018) and meteorological variables (Beck et al., 2019).

Table 2 Description of the global lake storage products.

Filename	Type of Volume	Satellite Sources	The Number of Measured Lakes	Period
Global_Lake_Absolute_Storage_LandsatPlusGREALM (1984-present).nc	Absolute	Landsat; G-REALM	67	1984-current
Global_Lake_Absolute_Storage_LandsatPlusICESat2 (1984-present).nc	Absolute	Landsat; ICESat-2	23,294	1984-current
Global_Lake_Absolute_Storage_LandsatPlusSentinel2 (1984-present).nc	Absolute	Landsat; Sentinel-2	4,054	1984-current
Global_Lake_Relative_Storage_LandsatPlusGREALM (1993-present).nc	Relative	Landsat; G-REALM	148	1993-current
Global_Lake_Relative_Storage_LandsatPlusICESat2 (2018-present).nc	Relative	Landsat; ICESat-2	23,419	2018-current

5. Conclusions

This study produced historical and towards near real-time lake storage dynamics from 1984-present using optical remote sensing (i.e., Landsat and Sentinel-2) and radar and laser altimetry data (i.e., Topex/Poseidon, Jason-1/2/3, Sentinel-3, and ICESat-2) at global scale. This product comprises both relative and absolute volume estimates for all HydoLAKES delineated lakes larger than 1 km^2. To achieve more frequent water extent measurements, a simple image gap-filling algorithm was implemented in each historical Landsat-derived surface water map. This process effectively solves missing data issues caused by, e.g., cloud, cloud shadow, swath edges and the Landsat-7 SLC failure. The monthly Landsat-derived water extents in this study show strong correlations with GRSAD v2 for 5,323 reservoirs, with an average R of 0.88. We demonstrated that the geo-statistical HydroLAKES bathymetry estimation approach produced slightly better results than the GLOBathy method. The geo-statistical method was applied to estimate absolute lake volume dynamics from 1984 onwards by combining Landsat and Sentinel-2 imagery. Validation results showed an average R of 0.78 and a SMAPE of 52.5% between estimated and reported volumes for 238 lakes in USA and Australia. In situ bathymetric measurements would be ideal to more precisely estimate total lake volume, but are not available for the majority of the millions of lakes globally.

Relative lake volume storage changes could be calculated for lakes where their satellite-derived extents and heights were both available. The average correlation between our relative storage product and a previous MODIS-derived data was 0.90. The historical lake storage time series can help improve understanding of the influence of climate change and human activities on global or regional lake storage dynamics from 1984 to present, and help to, e.g., estimate lake carbon dioxide and methane emissions from lakes. The NRT lake storage data we provide will hopefully provide useful and current information for water managers and other decision-makers in managing our water resources and aquatic ecosystems.

Author contribution. JH and AIJMVD conceived the idea. JH developed the methodology and software, carried out the investigation, curated the data and wrote the manuscript. AIJMVD, LJR, and PRL reviewed and edited the manuscript.

Competing interests. The contact author has declared that none of the authors has any competing interests.

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