GloLakes: ~~a database of global lake~~ water storage dynamics for 27,000 lakes globally from 1984 to present derived ~~using laser and radar~~from satellite altimetry and optical ~~remote sensing~~imaging

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Abstract. Measur~~ements of~~ing the spatiotemporal dynamics of lake and reservoir water storage ~~are~~ is fundamental ~~to~~for~~in the assessment of~~assessing 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 a few hundred~~s~~ ~~of~~ lakes worldwide and cannot estimate absolute (i.e., total ~~stored~~ volume) water storage. We increased ~~In this study,~~ the number of measured lakes ~~was increased~~ by a factor of ~~400~~ 300 by 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 and -6 instruments. Historical t~~T~~ime series (1984-2020) of ~~relative (i.e., storage change) or~~ absolute ~~(i.e., total stored volume)~~ storage could be derived 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~~ this data set~~satellite data~~, we investigated ~~where and for~~ how many lakes can be measured in near real-time ~~near real-time storages (2020-present) can be estimated by remote sensing~~ in ~~each~~ basins ~~around the~~ worldwide. ~~Then, w~~We ~~were able to~~ developed 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~~ from 1984 to current are publicly available through https://doi.org/10.25914/K8ZF-6G46 (Hou et al., 2022~~).~~) and a ~~These datasets are virtually displayed on the~~ web-based data explorer ~~application:~~ www.globalwater.online.

1. Introduction

Lakes and reservoirs are a key component of the global water cycle through their contribution to land-atmosphere exchanges, river-floodplain dynamics~~,~~ and groundwater systems. Lakes also emit substantial quantities of carbon dioxide and methane into 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~~ applications 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~~ However, 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 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~~ have benefitted from the substantial increase ~~of~~ in Earth observation technologies over the last four decades (Papa et al., 2022). ~~The r~~Remote sensinge ~~technologies and techniques~~ offers ~~a~~ monitoring capability with ~~a~~ coverage and consistency ~~that is~~ impossible to achieve with in situ networks (Alsdorf et al., 2007). ~~For example, t~~Most~~he large majority of~~ natural lakes are ungauged, perhaps because they are generally more significant to ecosystems and ~~for~~ biodiversity than for human activities and economic gain. ~~Many~~ Conversely, most large dam reservoirs~~, as capital investment constructions,~~ are gauged, ~~well~~ but these records are generally not publicly accessible. ~~All~~ This lack of in situ measurement ~~these issues~~ impedes understanding the change and variability of lakes worldwide. ~~Therefore, r~~Remote sensing provides ~~the best monitoring~~ a 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 toward~~s~~ 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~~overestimated. Lehner et al. (2011) ~~complied~~ compiled 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~~ by the International Commission on Large Dams (ICOLD), but most of them are still not georeferenced. This gap was addressed by the Global Georeferenced 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-3/6 instruments, has proven useful ~~to measure~~in measuring 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~~ their study was limited to around 200 lakes for which radar altimetry data ~~was~~ were 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~~227,386 lakes globally.

The spatial resolution of global satellite-derived surface 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~~ refined 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~~ sensor series ~~has~~ have 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 archives 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). Compared to

Surface water height and extent are the two basic ~~components to~~ measurements needed to determine water storage change in lakes and reservoirs. ~~The~~ Because of the shorter revisit times, daily or 8-day composite MODIS AQUA/TERRA products are less affected by cloud cover than 16-day Landsat observations, and ~~new~~ the ~~MODIS~~ imagesry ~~are~~ is updated ~~with~~ sufficiently rapidly ~~timeliness~~ to support near real time (NRT) water monitoring. Some studies have used MODIS-derived water extents and altimetry data to estimate lake storage changes, such as in 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 fails to detect changes in ~~a large majority of~~ smaller lakes, ~~of which~~ whose ~~the~~ number soars exponentially as ~~the~~ smaller lake sizes ~~deceases~~are considered. The 30-m resolution Landsat data, in combination with different altimetry sources, have been shown to be a better option ~~to estimate~~for estimating 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 the 1980s. Finally, while MODIS- or Landsat-derived water extent and altimetry data have demonstrated the capability to estimate changes in lake water storage, they cannot measure lake depth and, therefore, ~~are unable to~~cannot ~~measure~~ provide absolute water storage volume without ~~the use of~~using 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.~~Several studies (e.g., Avisse et al., 2017;Bonnema et al., 2016;Vu et al., 2022) used a digital elevation model (DEM) to derive height-area curves and estimate absolute water volume, but th~~is~~e success of this approach depends on ~~is affected~~ the volume of water present at the time of ~~by water level conditions at~~ DEM data acquisition~~-~~ (e.g., February 2000 for the Shuttle Radar Topography Mission DEM data often used)~~time~~. To circumvent this, 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~~Despite those approaches, there are currently no ~~such~~ data products that provide absolute lake volume ~~dynamics~~ estimates at the global scale.

~~This~~ The objectives of this study were to ~~aimed to~~ (1) ~~not only provides~~ derive nearly four -decades of data on relative and absolute water volume measurements for lakes worldwide and (2) ~~but also~~ enable~~s~~ a global~~,~~ NRT lake monitoring capability. To develop this, we f~~F~~irst~~, we~~ estimated water body extents between 1984-2020 from Landsat-derived surface water maps for 170,957 lakes. We applied the gap-filling algorithm (Hou et al., 2022) in ~~the~~ contaminated Landsat images to restore missing data, thus improving the total number of usable images to derive lake ~~water~~ area time series. Second, we estimated absolute water storage dynamics from 1984-2020 for each lake whose water area and its surrounding slope measurements are available using a geostatistical model (Messager et al., 2016). Third, as Landsat ~~can~~does not provide NRT observations, we considered a ~~bunch~~ range of ~~new~~ alternative satellite data sources (including Sentinel-2, Jason-3, Sentinel-3 and -6, and ICESat-2) with monitoring abilities to derive NRT absolute lake storage. We examined where and for how many lakes NRT storage can be estimated using different combinations of these remote sensing data in each basin ~~around the world~~worldwide. Fourth, we extended historical absolute water storage estimates to NRT monitoring using the volume-height relationship if radar or lidar altimetry data available after 2020. ~~If~~Where ~~there are~~ only NRT lake water area observations (~~i.e.,~~e.g., from Sentinel-2) were available, we converted lake area to storage estimates using ~~the~~a geo-statistical model. As these absolute lake storage products are affected by the bias errors of lake depth estimates from the geo-statistical model, we also provided relative lake storage ~~products~~estimates for lakes ~~that have been~~ observed simultaneously by optical ~~remote sensing~~ imagers and altimetry ~~instruments at the same time~~. Overall, this ~~study~~ ma~~k~~de i~~s~~t possible to monitor more than 27,000 lakes and reservoirs worldwide. ~~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 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~~ underlying strategy ~~to~~ in developing this global lake monitoring system ~~is~~ was to consider ~~different~~ all readily available~~kinds of freely accessible~~, validated, and frequently updated satellite data sources, ~~and to~~ explore the relative advantage of each ~~satellite~~ source, and combine them to 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 a 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~~ The monthly water history and monthly recurrence products from GSWD ~~are~~ were used ~~in this study~~here. The monthly water history product provides monthly water mapping from March 1984 to December 2020~~ and~~. ~~each~~ Each pixel was classified as open water, land, and non-valid observation. The monthly recurrence product comprises 12 ~~datasets~~ datasets, one for each month (from January to December). Each ~~dataset~~ shows the frequency of inundation in each pixel as a percentage of the number of times 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~~five-day ~~near real-time (~~NRT~~)~~ measurements of surface water extent from 2015 to the present for 8,837 lakes globally. The surface water map is derived using ~~normalized~~ normalised 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's surface. The six laser beams from ICESat-2 allow~~s it to cover more ground coverage of the Earth's surface, compared to~~ it to cover more ground coverage of the Earth's surface than its predecessor (ICESat-1). We used the ~~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 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).~~ATLAS/ICESat-2 L3A along-track inland surface water data, version 5 (ATL13) ~~was used in this study~~ (Jasinski and Ondrusek, 2021). ~~T~~Unfortunately, ~~he~~ updated ATL13 ~~product~~ data are ~~is~~ not released until 30-45 days after new observations ~~we~~are obtained, which does not ~~fit the purpose for the~~ suit NRT monitoring. Therefore, ~~in addition, we~~we also used ATLAS/ICESat-2 L3A Along Track Inland Surface Water Data Quick Look, Version 5 (ATL13QL), ~~which is~~ available within ~~3~~three days of new observations. ATL13 and ATL13QL apply the same algorithms to derive surface water height measurements for inland water bodies, including rivers, lakes, reservoirs and coastal water. The approach is described by Jasinski and Ondrusek (2021), but in brief, the procedure: 1) identifies ATLAS beams that intersect inland water body shape masks; 2) collects photons in short segments (~100 m) for calculating water height and in longer segments (1~3 km) for estimating and removing subsurface backscatter; 3) applies the physical and statistical modelling to derive inland water heights. Cooley et al. (2021) used ATLAS/ICESat-2 L3A Land and Vegetation Height (ATL08) to derive lake ~~water~~ height time series and found the mean absolute error between USGS gauge data and ICESat-2 height measurements is 0.14 m. Unlike ATL08, the ATL13 used ~~in this study~~here was designed to measure water height variations ~~o~~in rivers and lakes as it considers physical processes of light propagation in open water bodies. An error of 6.1 cm per 100 inland water photons has been reported (Jasinski and Ondrusek, 2021). We collected both ATL13 and ATL13QL water surface height data from any of the six beams within individual lake boundaries from HydroLAKES and derived water height ~~time series~~ for each lake ~~that~~ observed by ICESat-2 ~~from~~ between 2018 ~~to~~ and the present. ATL13QL has larger uncertainties (~100 m) in geolocation than ATL13 (~5 m). As a result, segment heights from ATL13QL are 2.7 m, with a standard deviation of ~ 7 m, lower than those from ATL13. According to the user guide (Jasinski and Ondrusek, 2021), 2.7 m can be added to ATL13QL before merging these two products, and the differences between them have little impact on measuring relative heights. Each lake will be revisited by ICESat-2 around every 91 days. This means our ICESat-2--based storage product is limited to provid~~e~~ing ~~updated~~ information on seasonal variation~~s,~~ rather than short-term ~~changes,~~ dynamics~~for global lakes~~. However, it has the benefit of provid~~es~~ing ~~updated data where there are new~~ observations with a rapid turnaround.

The Global Reservoirs and Lakes Monitor (G-REALM) provides NRT surface water height dynamics for ~~392~~ around 500 lakes globally using a combination of different satellite radar altimetry (Birkett et al., 2010). It ~~has~~ provides two on-going products~~:~~ (1)~~one is~~ ~~the~~ 10-day NRT water heights from 1993-present derived from ~~using~~ Topex/Poseidon, ~~and~~ Jason 1/2/3 and Sentinel-6, and (2) ~~the other is the~~ 27-day NRT water heights from 2016-present using Sentinel-3A and B. 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 within 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 geo~~-~~statistical model (Messager et al., 2016) is described as follows:

$$\mathrm{Log}_{10}(\mathrm{D}) = \mathrm{C}_1 + \mathrm{C}_2 \times \mathrm{Log}_{10}(\mathrm{A}) + \mathrm{C}_3 \times \mathrm{Log}_{10}(\mathrm{S}_{100}) + \mathrm{s}^2 \qquad (1)$$

where *D* is the predicted mean depth (m), *A* the observed surface area of the lake (km^2), S_{100} the average slope (derived from DEM) within a 100-m buffer around the lake, C_1, C_2 and C_3 ~~constant parameters~~coefficients estimated from ~~best~~ fitting the model using global lake data ~~and present~~ for different ~~for different sizes of~~ lakes sizes (i.e., 0.1-1 km^2, 1-10 km^2, 10-100 km^2, 100-500 km^2), and s^2 the residual variance. The fundamental assumption is that one can extrapolate the slope around the lake towards the centre of the lake to estimate lake depth. The traditional approach uses a DEM within the lake to derive A-H curves~~,~~ but cannot retrieve true land surface elevation below water. In comparison, the model used here considers the DEM outside lake rather than inside it~~,~~ and hence is not affected by water inundation at the time of DEM acquisition. Messager et al. (2016) reported that the symmetric mean absolute percent error between predicted and reference volume is 48.8% without significant bias in volumes for the majority of lakes around the world, with the exception of Finland, Sweden and northwestern Russia, the European Alps, and the Andes. ~~Before choosing this geo-statistical model, w~~We ~~did~~ compared this approach with alternative ~~different~~ approaches ~~to estimate lake depth~~. Khazaei et al. (2022) developed a statistical model, GLOBahty, relating lake depth with surface water area, elevation, volume, shoreline length, and watershed area. They demonstrated that the performance of this statistical model is better than ~~the~~ previous approaches to calculat~~e~~ing lake depth by ~~simply~~ assuming the lake shape fits one of ~~in~~ four geometries: box, cone, triangular prism, and ellipsoid (e.g., Yigzaw et al., 2018). ~~In our study, w~~We compared ~~this statistical model (Khazaei et al., 2022) with the geostatistical model (Messager et al., 2016)~~ both models ~~and validated them against~~ to in situ data. The resulting SMAPE error for the GLOBahty method was 70.5%, and therefore not better than the geo~~-~~statistical method. This result informed ~~led~~ our choice to use the simpler geo~~-~~statistical method in favour of the GLOBathy dataset in this study. The uncertainties from the geo~~-~~statistical model are mainly from the observed surface area and the DEM used to derive slope. The omission and commission errors of surface water mapping from GSWD used in this study are 5% and 1%, respectively. EarthEnv-DEM90 was used in the geo~~-~~statistical model to derive slope~~,~~ and its vertical accuracy is around 10 m (Robinson et al., 2014). We assessed how these errors propagate into water storage estimation in the validation analysis. ~~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 changes 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~~ ensure the maximum water extent possible was enveloped~~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 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~~ These factors ~~then~~ reduce~~s~~d the total number of effective Landsat images available over the 37 years~~ to derive water extent dynamics for many lakes~~. ~~Many~~ Previous studies ~~chose to either~~ used images with a contamination ratio below a certain threshold (e.g., 5%) or ~~to~~ aggregated the imagery ~~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~~ 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 we published previously (Hou et al., 2022) to recover~~y~~ missing data in partial Landsat water mapping to boost the total number of usable images. Unlike our earlier publication, however, ~~Hou et al. (2022), this study~~ we here used a ~~corresponding~~ monthly recurrence map~~,~~ rather than a multi-year average recurrence map~~,~~. This made it possible to restore the ~~contaminated~~ partially missing ~~water~~ maps for the specific month considered, ~~which~~ mak~~es~~ing it more sensitive to seasonal changes~~ as much as possible~~. In summary, the monthly GSWD recurrence product was used to ~~address~~ restore 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~~ using the January recurrence data. This ~~is~~ was 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 each contaminated image~~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~~ the mentioned geo~~-~~statistical model of Messager et al. (2016). ~~This model provides empirical equations (Eq. 1) 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~~ estimated monthly water storage dynamics from 1984-2020 for 170,611 lakes globally.

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~~satellite sources, including ICESat-2~~the National Snow & Ice Data Center (NSIDC)~~, U~~.S.~~S Department of Agriculture (USDA) GREALM and BLUEDOT (Sentinel-2) water observatory (Table 1). We selected all ~~measurements~~ estimates for lakes whose volume dynamics from 1984–2020 were derived from GSWD with the geo~~-~~statistical model. ~~As there are~~We examined pairwise relationships (i.e., *V-H* or *V-A*) of 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 extended historical volume estimation to NRT monitoring ~~applied this method~~ when there was a statistically significant~~ly~~ (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~~2020.

~~Considering different~~Depending on some of the features of the satellite data sources (Sentinel-2, ICESat-2, GREALM) ~~with monitoring abilities~~, we used different approaches to estimate absolute NRT storage ~~time series~~. If both historical and NRT ~~satellite~~ sources (i.e., Landsat and Sentinel-2) only observed lake ~~surface water~~ area changes, we converted lake area to storage using the geostatistical model (Eq. 1) and merged them ~~together~~ to derive storage time series from 1984-present. If NRT satellite sources (i.e., ICESat-2 or GREALM) ~~can~~ observed lake water height changes, we developed the relationship ~~of the overlapping monthly time series~~ between historical volume (*V*) and NRT height (*H*) for the overlapping months and used ~~their~~ that *V-H* ~~pairwise relationship (i.e., *V-H*)~~ to extend historical volume estimation to NRT monitoring using only satellite-derived *H*. As the relationship is not necessarily ~~monotonic~~linear, NRT lake storage~~s~~ ~~were~~ was estimated using cumulative distribution function (CDF) matching. ~~In practice, a~~A look-up table was developed to rank all historical *H* and *V*, allowing one to be estimated from the other based on the ranking. ~~In total~~Overall, we derived ~~estimated~~ absolute water storage dynamics from 1984 onwards for 24,865 lakes using ICESat-2, 129 lakes using GREALM, and 4,054 lakes using Sentinel-2.

~~The~~ Our main objective ~~main purpose in this study is~~ was to estimate NRT absolute water storage dynamics for lakes worldwide as much as possible ~~around the world~~. ~~But~~ However, we also measured relative storage ~~estimates~~ where ~~both~~ radar or laser-derived surface water heights ~~as well as Landsat-derived surface water extent~~, as well as Landsat-derived surface water extent,~~s~~ were available (i.e., Landsat ~~and~~ with ICESat-2 or Landsat ~~and~~ with GREALM). ~~Different~~ Unlike ~~from~~ absolute storage products, relative storage products ~~were~~ are un~~not~~ affected by any bias ~~errors~~ from the geostatistical model. ~~In this study, w~~We produced alternative ~~varieties of lake~~ storage datasets~~, thus~~ to provid~~ing~~e ~~more~~ options to ~~the~~ users requiring ~~with~~ different bias tolerances ~~in~~ or different applications. For the relative storage products, we calculated historical storage changes for lakes where the A-H relationship was significantly correlated as follows (Crétaux et al., 2016):

$$\Delta V = \frac{(H_t - H_{t-1}) \times (A_t + A_{t-1} + \sqrt{A_t \times A_{t-1}})}{3} \qquad (2)$$

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 $t-1$, respectively. ~~T~~Where there are only H data available in the NRT period, we estimated corresponding A using CDF matching and calculated relative storage change time series using ~~the~~ Eq (2). As Sentinel-2 and ICESat-2 can measure NRT surface water extent and level, respectively, we used them to derive relative storage changes from 2018-present. This product is free from ~~the~~ any errors ~~form~~ in ~~both~~ the geostatistical model and in the *A-H* or *V-H* relationships used in the other products. Overall, we measured relative lake storage dynamics from 2018 onwards for 24,990 lakes using ICESat-2 and Landsat, for 2740 lakes using ICESat-2 and Sentinel-2, and from 1993 onwards for 227 lakes using GREALM and Landsat.~~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~~ storage monitoring using ~~that have~~ observations overlapping with the Landsat-derived water extent dataset.

Dataset	I	II	III
~~Platform~~	~~NSIDC~~	~~USDA~~	~~BLUEDOT~~
Source	ICESat-2	USDA G-REALM ~~(several satellites)~~	BLUEDOT (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~~347	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):~~

~~$\Delta V =$ — (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 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 Lake area estimation validation~~Improved lake extent mapping after image gap-filling~~

A large portion of Landsat data ~~were~~ was missing due to cloud, cloud shadow and the Landsat-7 Scan Line Corrector (SLC) failure. ~~Unmitigated~~Left unmitigated, this issue would have ~~resulted in the~~ limited the ~~number of~~ observations per year or an underestimation of surface water area even if using ~~an~~ images with ~~a low~~ little contamination ~~ratio~~. Cloud cover ~~is~~ was the most common issue, but water extent could be reconstructed for contamination ratios of 58% and higher (Fig~~s~~. 1 and Fig. S1~~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 (Fig~~s~~. 1 and Fig. S1~~2~~). The reconstructed water extent maps in the rightmost column of Fig~~s~~. 1 and Fig. S1~~2~~ demonstrate that these missing data scenarios could be usefully restored, no matter what types of contamination issues, what kinds of lake shapes, or how much (between 5-70%) of contamination ratios. By applying this step, we ~~much~~ strongly increased the number of ~~effectively~~ usable~~useful~~ images.

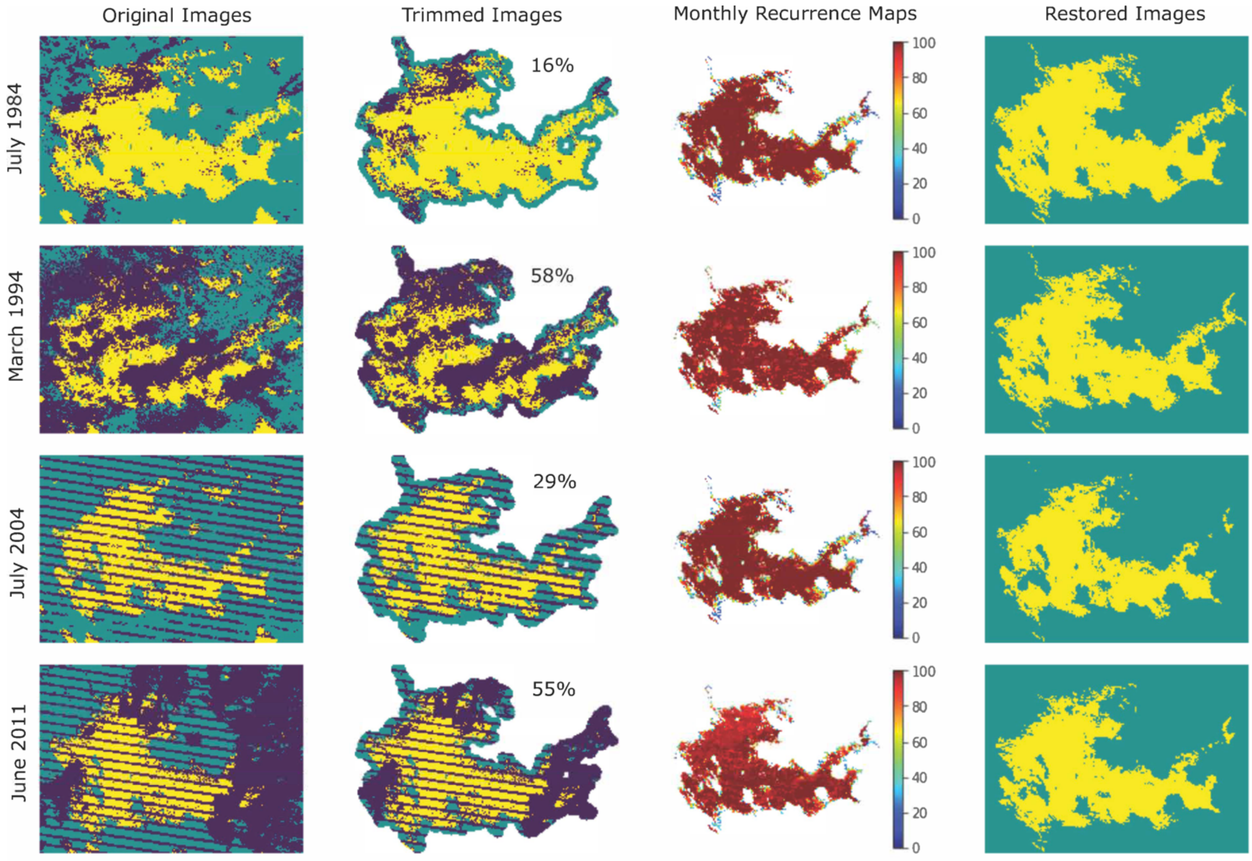


Figure 1. Examples of the performance of the image gap-filling algorithm in Lake Rossignol, Canada. (First column: historical water maps from GSWD (yellow: water; green: land; blue: no data; image contaminated ratio from top to bottom: 16%, 58%, 29% and 55%); second column: historical water maps trimmed 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)

Our lake area data have 5318 lakes in common with the data of Zhao and Gao (2018)~~,~~ and 11,101 lakes with Donchyts et al. (2022) with ~~. The lakes for which area estimates were validated had~~ average areas from 0.1 km^2 to 1000 km^2. Zhao and Gao (2018) used the same Landsat data source (GSWD) and the same lake boundary delineation (GRanD included in HydroLAKES) but a different gap-filling approach to derive lake area. Nonetheless, the mean lake area between the two products scatters closely around a 1:1 relationship (Fig. 2a). ~~In addition, w~~We also calculated correlation and bias in lake area time series for the common period 1984–2018 for each lake. The median R and SMAPE were 0.91 and 3.6%, respectively. This suggests that ~~that~~ our gap-filling algorithm produces results ~~that are~~ overall similar to those of Zhao and Gao (2018). Donchyts et al. (2022) used a different Landsat data source, lake boundary delineation, and gap-filling algorithm to derive lake area time series. Despite these differences, mean lake area values still ~~lies~~ cluster fairly closely around the 1:1 relationship, especially for lakes greater than 1 km^2 (Fig. 2b). Larger biases exist for some lakes smaller than 1 km^2. This was caused mainly by different definitions of lake boundaries between HydroLAKES and Donchyts et al. (2022); we found that only one-tenth of lakes had boundary area differences within 20%. The median R and SMAPE in lake area time series from 1984 to 2020 for 11,101 lakes between our product and Donchyts et al. (2022) were 0.76 and 9.7%., once again lower mainly due to the differences for small lakes.

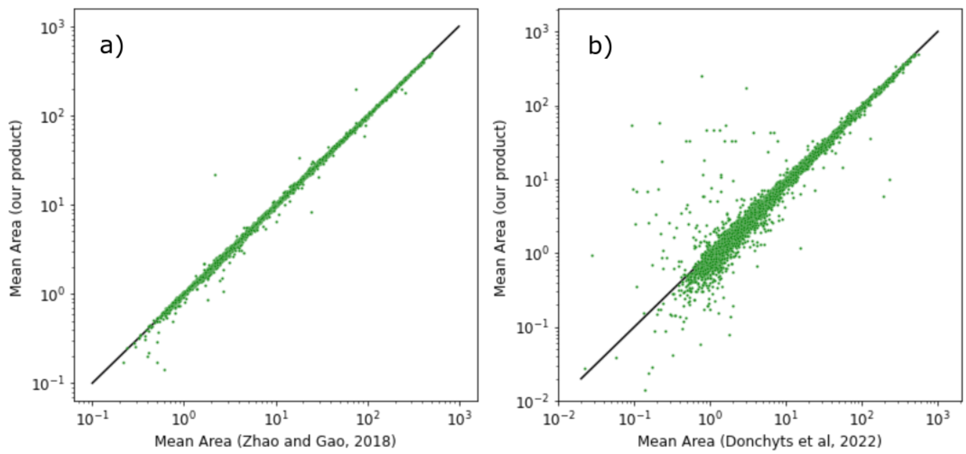


Figure 2 Scatterplots of mean lake area from our product vs. two other published datasets (black line: 1:1 relationship).

3.2 ~~Where~~ Feasibility of near real-time lake monitoring ~~is feasible~~~~Coverage~~

We ~~were able to estimate~~estimated monthly lake volume dynamics for 170,611 lakes ~~for~~ during ~~the period~~ 1984–2020 (Fig. 3a). Most ~~of them~~lakes are ~~distributed across~~ in the northern hemisphere's ~~high~~ high latitude~~s regions~~, especially in ~~northern~~ North America. ~~The GloLakes dataset also provides near real-time volume estimates for 27,599 lakes.~~ We only considered ~~all~~ lakes with an area greater than 1 km^2 given the resolution ~~limitations~~ of the Landsat imagery. There are more than a million lakes with areas between 0.1–1 km^2 that remain unmeasured, but the combined storage of these small lakes only accounts for 1% of global total lake water storage, according to the HydroLAKES dataset. Overall, ~~the~~ a large ~~vast majority~~portion of global lake volume for the period 1984-2020 ~~has been~~was 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).~~ ~~This~~ Here we ~~study mainly~~ focuse~~s~~ on estimating both historical and NRT lake ~~water storage~~ dynamics. NRT lake water storage ~~time~~

~~series were~~was only estimated if A-H-V relationships were ~~significantly correlated~~sufficiently strong, ~~al~~even though we produced historical water storage change for more than 170,000 lakes. This also ensures ~~means we make sure~~ that satellite-derived extent and level observations are consistent in characterising lake change before producing lake storage time series from 1984 to the present.

As the Landsat, Sen~~i~~tinel-2 and ICESat-2 ~~used here~~ have comprehensive coverage of global lakes, we investigated if ~~we can use~~ any two of them (optical + altimetry or two optical) can be used to monitor global lakes and ~~for~~ how much of the lakes in each basin storage can be measured in ~~by remote sensing~~each case. This should provide valuable information for the newly launched Surface Water and Ocean Topography (SWOT) mission that aims to monitor~~s~~ storage changes in global lakes ~~as it achieves to~~ by measure~~e~~ing both extent and level on a single satellite platform. 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~~ spatial basin units for ~~lake statistical~~ analysis~~ in this study~~. ~~This should provide valuable information for the newly launched Surface Water and Ocean Topography (SWOT) mission that monitors storage changes in global lakes as it achieves to measure both extent and level on a single satellite platform.~~ If remote sensing measurements from two sources (derived extent and level or derived storages) are significantly correlated for a particular lake, we considered that this lake can be monitored by Earth observation. We followed three compl~~i~~ementary approaches: (1) geo-statistical model (Landsat + Sentinel-2), (2) *H-V* relationships (Landsat + ICESat-2), and (3) extent and level observations (Sentinel-2 + ICESat-2). Approach (3) ~~can be considered~~ would likely be the most reliable as storage~~s~~ is ~~were~~ directly measured by extent and level from remote sensing. However, approaches (1) and (2) make it possible to estimate absolute storage changes. Landsat and ICESat-2 together ~~are able to~~ could measure lake water storage in nearly all (i.e., 234 out of 292) river basins worldwide (Fig. 3b). Satellite-derived extents and levels are significantly correlated for ~~over~~ more than one-fourth of lakes in each of the 145 basins. This feature is evenly distributed across the continents, except for Antarctica and ~~northern high~~high northern- latitudes~~, regions,~~ due to the influence of frozen water surfaces. Sentinel-2 and ICESat-2 cover 122 basins globally (Fig. 3d). There are 58 basins where over half of the lakes can be monitored by ~~them~~that method, mainly located in the USA, southeastern South America, the Mediterranean, southern Africa, southern Asia, and Australia. Landsat and Sentinel-2 both measure surface water extent and ~~they~~ show strong time series consistency in 63 out of 124 basins. Three-quarters of lakes ha~~s~~ve a significant *A-H* relationship (Fig. 3c) with a distribution pattern similar to that of Sentinel-2/ICESat-2.

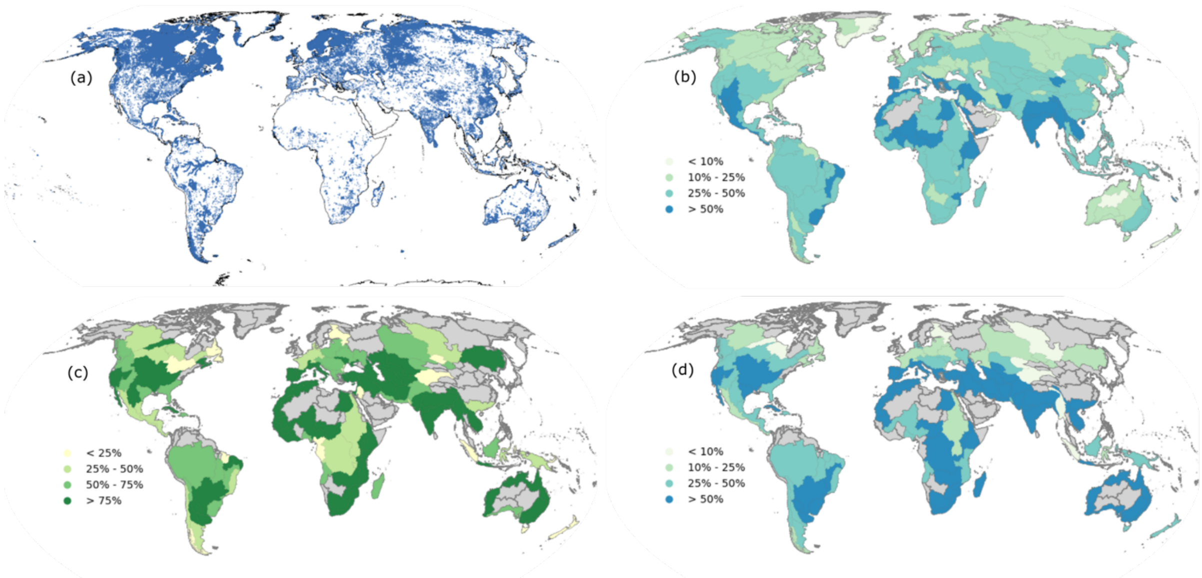
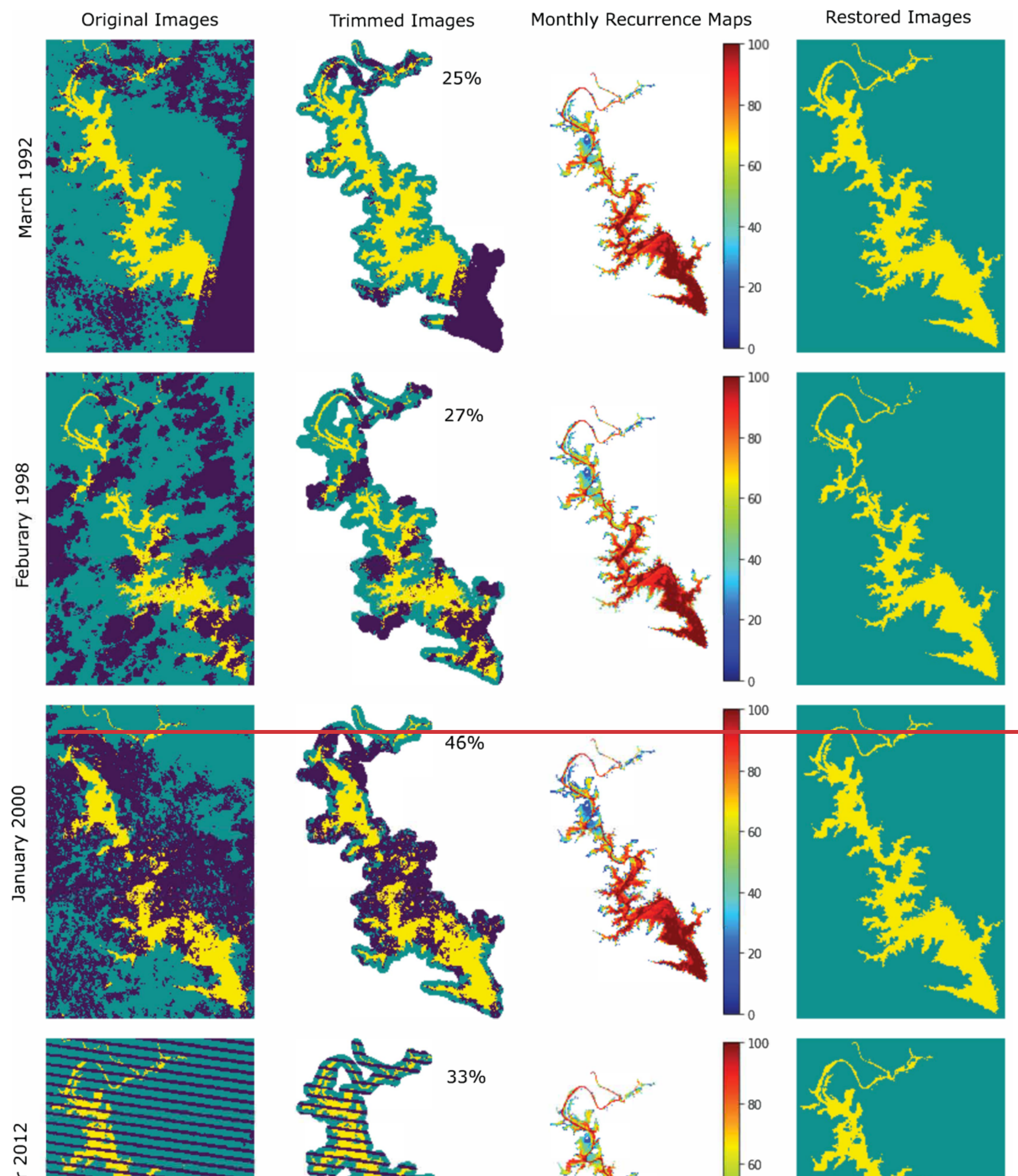


Figure 3 The locations of 170,~~957~~611 lakes whose storage dynamics for the period of 1984-2020 were estimated in this study (a), the percentages of lakes (in terms of number) whose NRT water storage dynamics can be derived using Landsat and ICESat-2 (b), Landsat and Sentinel-2 (c), and Sentinel-2 and ICESat-2 (d) in each basin.



~~**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)~~

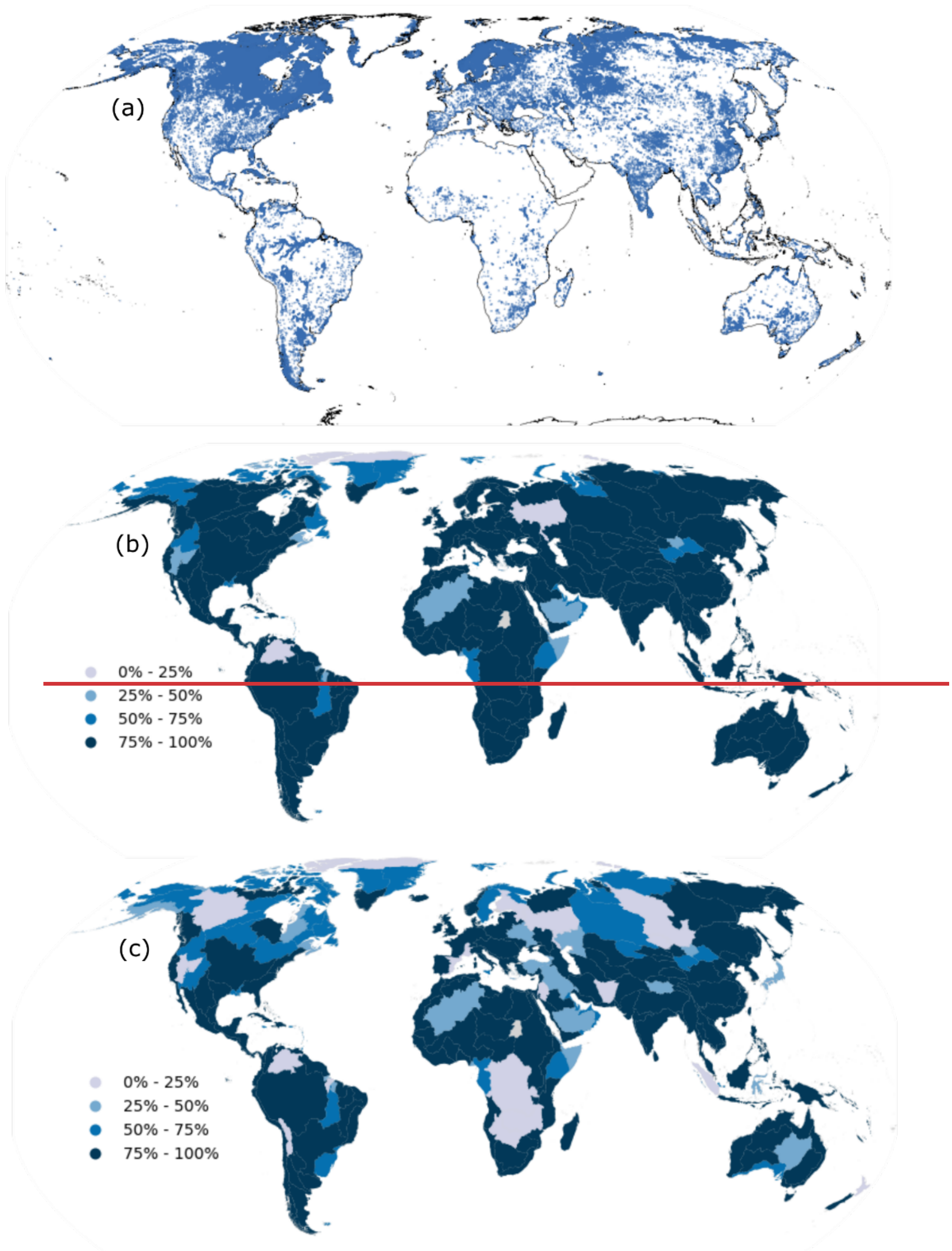


Figure 3 ~~a) The locations of 170,957 lakes whose storage dynamics for the period of 1984-2020 were measured in this study, b) the ratio (%) of measured extent or/and height (covert to volume) in this study and total volume recorded in HydroLAKES, and c) the ratio (%) of measured volume in this study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

3.3 Validation of historical lake storage estimates~~Validation~~

There is a general lack of independent and publicly available lake and reservoir storage data ~~with which~~ to validate our results, and indeed the lack of on-ground data motivated our study. Nonetheless, we were able to validate absolute lake volume ~~time series~~ estimates against in situ measurements for ~~238~~ 494 lakes in Australia~~,~~; South Africa, India~~,~~ and Spain; and the USA, respectively available from the Australian Bureau of Meteorology, Donchyts et al. (2022), ~~and~~ United States Bureau of Reclamation and United States Army Corps of Engineers~~, respectively~~. We evaluated the accuracy of lake volume time series by Pearson correlation (R) and the symmetric mean absolute percent error~~-~~:

$$SMAPE = 100 \times \frac{1}{N} \sum \frac{|observed\ volume - predicted\ volume|}{(observed\ volume + predicted\ volume)/2} \qquad (\cancel{2}3)$$

The results (Fig. 4) suggest a~~n~~ ~~average~~ median R between reported lake volumes and our estimates of ~~0.78~~0.91 and a SMAPE of ~~52.5~~38%. This SMAPE is similar to the 48.8% ~~that~~ reported ~~in~~ by Messager et al. (2016) ~~(48.8%)~~. Some 82% of validated lakes have R above 0.7 and SMAPE ~~values mainly~~ ranges between 5%~~-~~–50% (Fig. 4). ~~Selected lake volume c~~Comparisons for selected lakes are shown in Fig.~~4~~5, ~~chosen to~~ representing different sizes of lakes and different SMAPE errors. It appears ~~We can also see~~ that uncertainties from remote sensing and the DEM do not meaningfully ~~significantly~~ affect absolute lake volume estimates and that bias is the main source of error ~~-~~(Fig. 5). The lakes for which storage was validated had average volumes ~~from~~ between 1~~-~~ and 10,000 GL (Fig. 6). The comparisons ~~of mean lake volumes~~ between GloLakes and in situ data show that the bias error (38%) is consistent ~~along with~~for different lake sizes (Fig. 6).

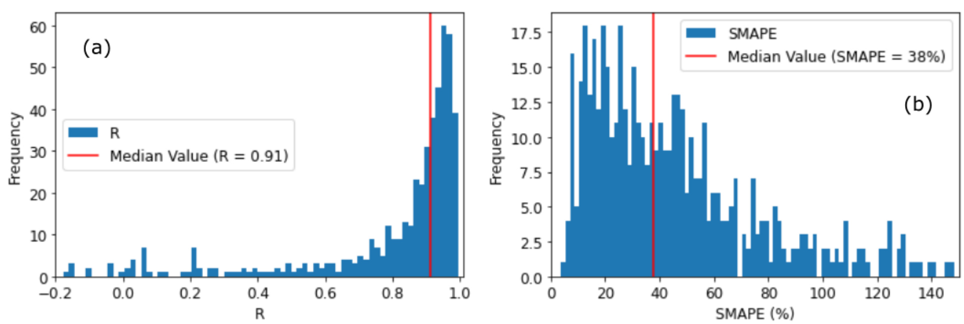


Figure 4 The distribution of R and SMAPE of absolute water storage validation results against in situ data for 494 lakes (vertical red line: the median value).

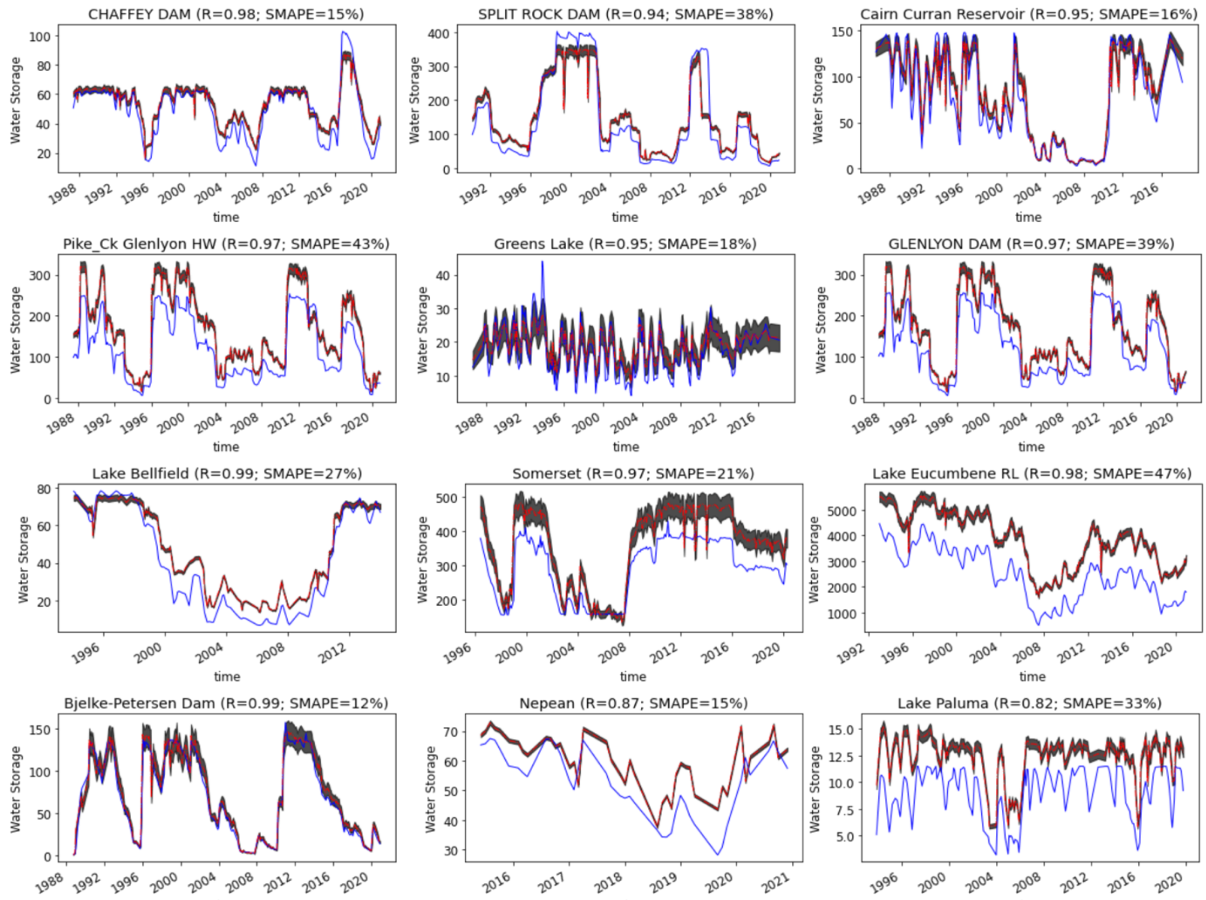


Figure ~~4~~ **5** ~~Some~~A ~~comparisons of a~~bsolute lake water storage time series from GloLakes against in situ (observed) data for selected lakes (blue line: observed data; red line: historical storage estimates; black shade: error bars of historical storage estimates).~~Some comparisons of predicted lake water storage from GloLakes against in situ (observed) data..~~

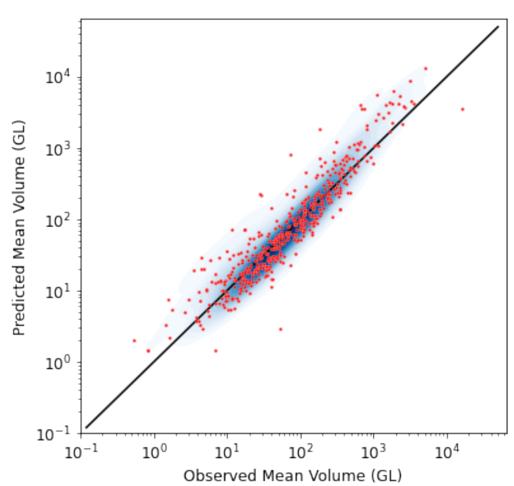


Figure 6 Scatterplots of predicted mean lake volume vs. observed mean volume (red dot: mean lake volume; black line: 1:1 relationship; background blue colours indicate data density).

For many applications, the relative agreement (e.g., *R*) may be more relevant than the absolute error, ~~as~~ and the latter can be affected by several factors. For example, the delineation of lake shorelines from HydroLAKES can be different ~~than~~ from those used for in situ measurement, as the spatial definition to distinguish the lake from connected rivers or wetlands can ~~in practice~~ sometimes be ambiguous. ~~As a result~~In such cases, 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~~with high accuracy 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. T~~. T~~he ~~estimation~~ accuracy of that approach ~~largely~~ depends on the quality of the DEM ~~used~~ and the degree to which the relationship between the topography of the lakebed and ~~the~~ surrounding slopes ~~surrounding the lake~~ conforms to the geostatistical model assumptions~~is such that the underlying assumptions are supported~~. ~~Overall, t~~The relative volume ~~dynamics~~ estimates 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.~~ We compared our relative lake storage dynamics data against the global surface water storage change time series for 1992–2018 ~~The data~~ produced by Tortini et al. (2020) for 104 common lakes. The data ~~can be~~ was 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~~ two show strong agreement (Fig. 7) ~~showed that the two datasets have a strong agreement,~~ with a median *R* of 0.94 ~~(~~ and 95% of ~~them~~ R values above 0.7~~)~~. Selected ~~Some of the~~ time series are compari~~soned~~ ~~results are shown~~ in Fig. 8~~.~~ and show that both datasets are most limited by the temporal frequency of image acquisition.

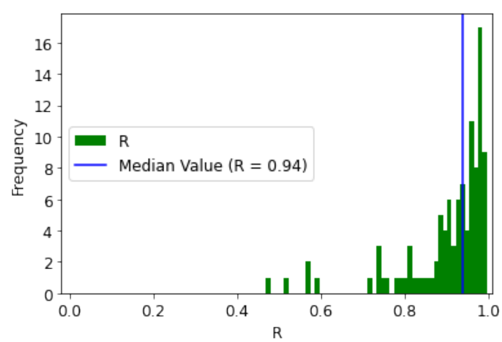


Figure 7 The distribution of R of relative water storage validation results against Tortini et al. (2022) for 104 lakes (vertical blue line: the median value).

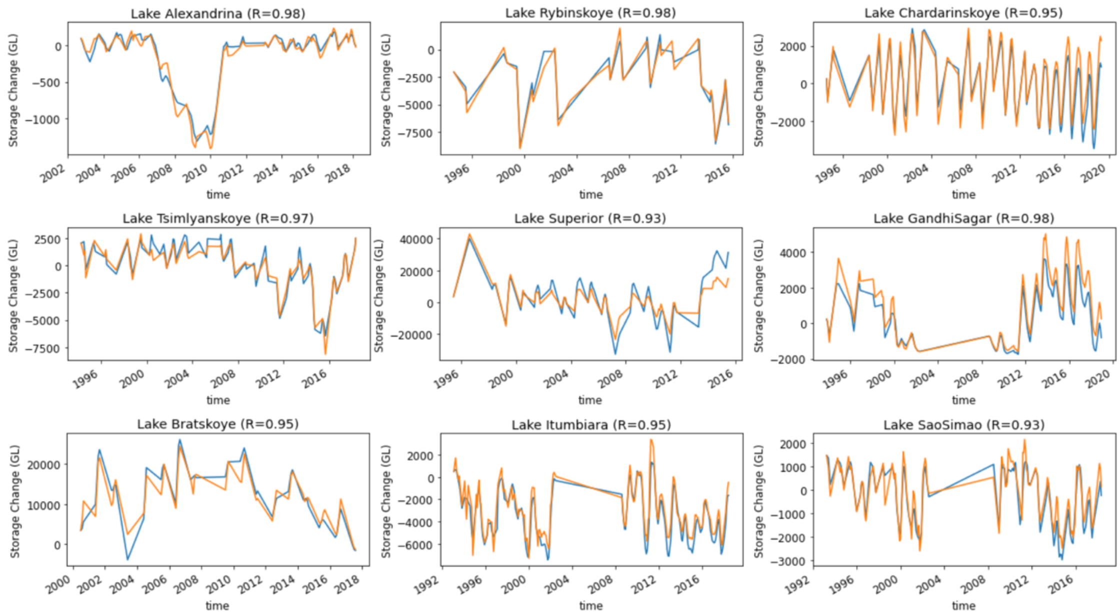


Figure 8 Relative lake water storage time series from GloLakes (blue line) against Tortini et al. (2022) (brown line) for selected lakes.

~~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 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.~~

3.4 Validation of NRT lake storage estimates

To our knowledge, we produced the first four decades-long data set of relative and absolute lake storage dynamics from 1984-present for all HydroLAKES registered lakes with an 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~~. Similarly, Tortini et al. (2020) produced a storage change dataset for 347 lakes ~~in a similar way~~ but using MODIS instead of Landsat imagery. ~~Furthermore, n~~Neither study offered ~~one of these studies tested~~ an 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 monitor a wide range of lakes at global scale.

We validated our ICESat-2 ~~derived~~ and Sentinel-2 derived water storage time series from 1984 to present against in situ data that ~~contains~~ can help to assess the accuracy of both our historical and NRT ~~observations~~ methods (Fig. 9). We compared the performance of water storage estimates between the respective methods used to derive historical and NRT ~~periods~~estimates ~~to investigate if extrapolated NRT estimates are valid~~. The average R and SMAPE ~~in~~ for the ~~historical~~ method, evaluated for ~~period (~~1984-2020~~)~~ ~~if~~ with storage ~~was~~ estimated using a geostatistical model, ~~-~~were 0.94 and 22%. The performance for the NRT ~~period~~ method, evaluated for ~~(~~2020-present~~)~~ with ~~when~~ storage ~~was~~ estimated using a *V-H* relationship or *V-V* merging, decreased slightly ~~(~~to *R*=0.88 and SMAPE=31%~~)~~, respectively. For most lakes, the agreement between predicted and observed storages ~~in NRT period~~ shows similar accuracy (in terms of correlation and bias, Table 2) for the historical and NRT methods, as NRT ~~storages~~ estimates were ~~in our products were~~ only ~~estimated~~ produced if the *V-H* or *V-A* relationships were significantly correlated. For example, both ICESat-2 and Sentinel-2 derived products record sharply decreasing in water storage in Big Sandy Reservoir, Vega Reservoir, and El Vado Lake in the NRT method period (Fig. 9). However, the performance ~~for~~ of the NRT ~~period~~ method ~~statistically~~ decreases for Lake Summer, Horsetooth Reservoir and El Vado Lake as there ~~is~~was one erroneous observation (Fig. 9).

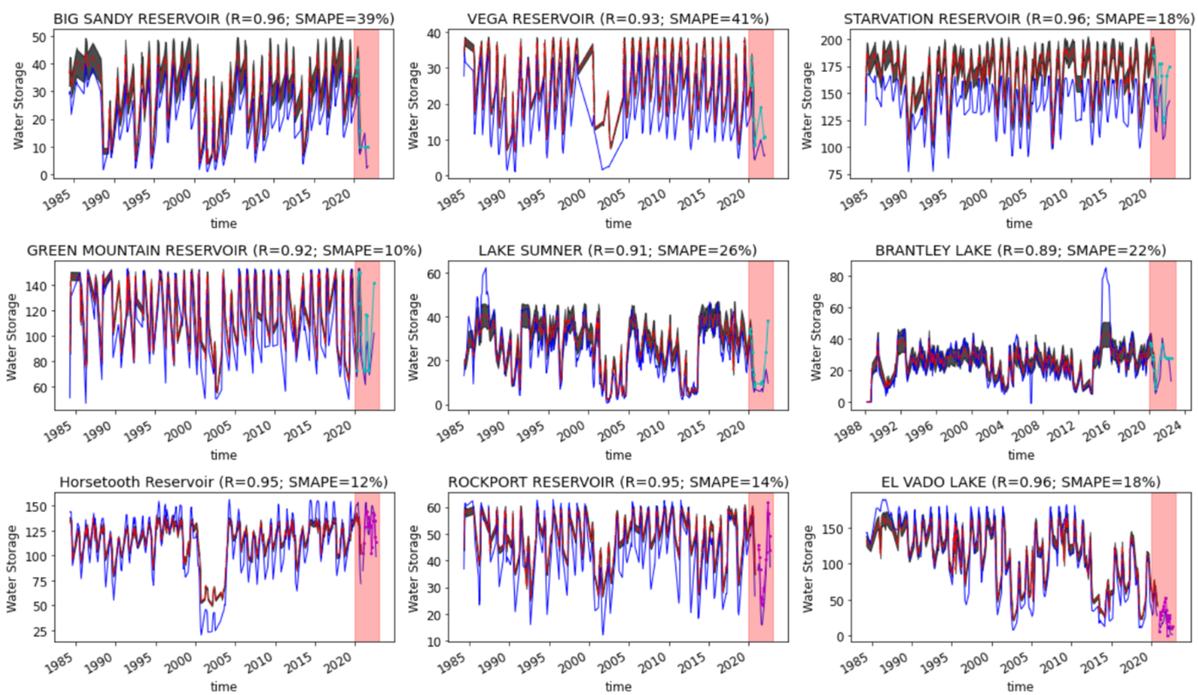


Figure 9 Comparisons of historical and NRT lake water storage time series from GloLakes against in situ (observed) data (blue line: observed data; red line: historical storage estimates; black shade: error bars of historical storage estimates; light pink shade: NRT monitoring period; cyan line with dots (first two rows): NRT storage estimates from ICESat-2; magenta line with dots (third row): NRT storage estimates from Sentinel-2).

We compared NRT estimates from our different storage products (ICESat-2, Sentinel-2, and GREALM)~~,~~ and summari~~z~~sed the results for lakes ~~with~~of different sizes (Table 3). The mean *R* and SMAPE between ICESat-2 and Sentinel-2 products w~~as~~ere 0.83 and 7%, respectively. The ICESat-2 and GREALM products had a similar correlation (*R*=0.81) and bias

(SMAPE=7%), although they are both derived from altimetry. The evaluation results generally did not vary ~~as a function of~~ with lake size, except ~~for the fact~~ that ICESat-2 and Sentinel-2 products show better correlation (R=0.92) and less bias (SMAPE=2%) for lakes with an area greater than 100 km^2.

Table 2 Comparisons of correlations and biases between historical and NRT methods (results from Fig. 9).

Lake Name	NRT Monitoring Approach	Historical (1984-2020)		NRT (2020-present)	
		R	SMAPE	R	SMAPE
Big Sandy	L-H; ICESat-2	0.96	39%	0.94	53%
Vega		0.93	41%	0.98	52%
Starvation		0.96	18%	0.97	18%
Green Mountain		0.92	10%	0.93	13%
Sumner		0.91	26%	0.81	43%
Brantley		0.89	22%	0.89	21%
Horsetooth	L-A; Sentinel-2	0.95	12%	0.56	8%
Rockport		0.95	14%	0.99	19%
El Vado		0.96	18%	0.81	48%

Table 3 Cross-validations of NRT method between our different storage products for lakes ~~with~~ of different sizes.

	Landsat + ICESat-2							
	Landsat + Sentinel-2				Landsat + GREALM			
	<10 km^2	10-100 km^2	>100 km^2	All	<10 km^2	10-100 km^2	>100 km^2	All
Total number of overlapped lakes	1247	612	92	1951	7	22	63	92
R	0.83	0.83	0.92	0.83	0.84	0.84	0.80	0.81
SMAPE	8%	7%	2%	7%	7%	11%	5%	7%

3.5 Future opportunities ~~to monitor lake storage changes~~

Remote sensing provides an opportunity ~~can~~ to measure water in ~~the majority lakes worldwide and provide NRT information, which is not~~ most lakes worldwide and provide NRT information, which is impossible with the current in situ network. ~~Both~~ Topex/Poseidon (1992-2002), ~~and~~ Jason 1/2/3 (2002-present), and Sentinel-6 (a.k.a. Jason-CS; 2020-present) are all able to measure lake height every ~~10~~ ten days, which can be adequate to ~~trace~~ monitor ~~the variability of~~ lakes dynamics. ~~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 altimeter~~these radar altimeters cannot detect many smaller lakes in between the sparse ground tracks. The ICESat-2 laser altimeter can cover ~~a much larger number of~~many more 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 many lakes,~~,~~ and more frequent water extent mapping can be used to interpolate between these observations. Th~~e Landsat-derived GSWD was used to estimate lake surface water extents from 1984-2020 in this study~~is study used the Landsat-derived GSWD to estimate lake surface water extents from 1984-2020. The GSWD are expected to ~~will~~ be updated annually by the Joint Research Centre of the European Commission (https://global-surface-water.appspot.com/download), ~~meaning~~ at which point lake extent estimates can be extended beyond 2020. Although Landsat ~~is not able to~~cannot 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~~ candidate for NRT global lake monitoring,~~,~~ ~~but~~ although the sheer volume of data presents ~~some~~ challenges for storage and ~~easy access~~processing. ~~L~~Sentinel-2-based lake ~~water~~ area data ~~from BLUEDOT~~ are currently already ~~only~~ available from BLUEDOT for several thousand lakes ~~around the world~~worldwide, and ~~, although its satellite source is Sentinel-2. In fact~~there is no fundamental limitation that would prevent a similar approach from measuring all ~~, Sentinel-2 can observe surface water changes for the same amount (e.g.,~~ 170,957 lakes measured ~~in this study) of lakes as~~ by Landsat in this study. The advantage of ~~using~~ Sentinel-2 ~~is~~ would be that it can provide NRT lake observations with low latency. ~~However, it requires huge~~ The high computation and storage demands can ~~computation sources to derive global lake water area change even in one repeat cycle as it has high spatial and temporal resolution. This limitation can be~~ potentially be ~~addressed~~ met by ~~the existence of~~ cloud platforms like Google Earth Engine (GEE). In future research, we ~~We~~ hope ~~will~~ to consider such approaches to ~~GEE and Sentinel-2 to~~ improve ~~monitoring abilities~~our data set ~~of our GloLakes product in the future study~~. ~~The~~ An inherent ~~main~~ limitation of ~~using~~ any optical remote sensing is the effect of cloud~~-~~s and other atmospheric interferences and vegetation, to a lesser extent~~, vegetation~~. This issue ~~can~~ could be mitigated by using passive microwave sensors or SARs. ~~The~~ For example, 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~~ differences 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~~ Finally, the Surface Water and Ocean Topography (SWOT) satellite mission ~~will be~~~~has been~~ was launched at the end of 2022~~, which~~ and ~~will~~ ~~can~~ is expected to measure surface water height and extent simultaneously every ~~21~~ 11 days for lakes greater than 250 m by 250 m. Its temporal resolution ~~sits~~ is intermediate to ~~between~~ the radar and laser altimetry used ~~in this study~~here. The spatial resolution is lower than Landsat and Sentinel-2, but

SWOT shows promise for monitoring lake changes given that the two basic components (i.e., *A* and *H*) needed to estimate lake volume change are measured ~~at the same time~~simultaneously.

4. Data availability

The ~~global historical and near real-time lake storage~~GloLakes data described here are available from https://dx.doi.org/10.25914/K8ZF-6G46 (Hou et al., 2022). ~~Five~~ Six products are provided, ~~the details of which are listed~~ described in Table ~~2~~4. ~~Our~~ The products also provide additional attributes ~~including~~ such as latitude, longitude, lake name, country name, state/province name, basin name and catchment name for each lake. The products can be linked to the HydroLAKES database using the ID index provided in the metadata. This allows users to combine storage dynamics data with other lake attributes, such as ~~latitude, longitude,~~ lake type, shoreline length, hydraulic residence times, and watershed area, ~~etc~~among others. Using the same HydroLAKES metadata, ~~our~~ the data~~set~~ can also be coupled to the GRanD (Lehner et al., 2011), HydroSHEDS (Lehner et al., 2008), and HydroRIVERS (Lehner and Grill, 2013) data~~-~~bases. ~~Thus~~This allows ~~,~~ users ~~can~~ to ~~access~~ relate ~~additional~~ other river and reservoir ~~information~~ attributes and implement the data in hydrological model configuration, e.g., to improve river routing. The global lake dynamics ~~are also~~ can also be interactive explored ~~accessible and visualised~~ through the Global Water Monitor (http://www.globalwater.online~~the web address will be released soon~~), which along with NRT information on other water cycle data such as ~~, among others,~~ river discharge (Hou et al., 2020;Hou et al., 2018), soil moisture (https://cds.climate.copernicus.eu/cdsapp#!/dataset/10.24381/cds.d7782f18?tab=overview, v202012 combined product) and precipitation and other meteorological variables (Beck et al., 2022) ~~(Beck et al., 2019)~~.

Table ~~2~~ 4 Description of the ~~global lake storage~~GloLakes 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~~129	1984-current
Global_Lake_Absolute_Storage_LandsatPlusICESat2 (1984-present).nc	Absolute	Landsat; ICESat-2	~~23,294~~24,865	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~~227	1993-current
Global_Lake_Relative_Storage_LandsatPlusICESat2 (2018-present).nc	Relative	Landsat; ICESat-2	~~23,419~~24,990	2018-current
Global_Lake_Relative_Storage_Sentinel2PlusICESat2 (2018-present).nc	Relative	Sentinel-2; ICESat-2	2740	2018-current

5. Conclusions

~~This study~~ We produced historical and ~~towards~~ near real-time lake storage dynamics from 1984-present by combining ~~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-3/6, and ICESat-2) at the global scale. 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 the 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~~ those managing our water resources and aquatic ecosystems. ~~This product comprises both relative and absolute volume estimates~~Surface water extent time series were estimated for all ~~HydoLAKES~~ HydoLAKES-delineated lakes larger than 1 km^2. To maximise ~~achieve more frequent water extent~~ measurement~~s~~ frequency, a simple image gap-filling algorithm was implemented in each historical Landsat-derived surface water map. This process effectively ~~solves~~ restored 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~~ showed strong correlations with ~~GRSAD v2~~Zhao and Gao (2018) for ~~5,323~~ 5,318 reservoirs and Donchyts et al. (2022) for 11,101 lakes, with a~~n~~ ~~average~~ median R of ~~0.88~~0.91 and 0.76, respectively. ~~We demonstrated that t~~The geo-statistical HydroLAKES bathymetry estimation approach produced slightly better ~~results~~ volume estimates than the GLOBathy method~~. The geo-statistical method~~ and was applied to estimate absolute lake volume dynamics from 1984-2020 for 170,611 lakes~~-onwards by combining Landsat and Sentinel-2 imagery~~. Validation results showed a~~n~~ ~~average~~ median R of ~~0.78~~0.91 and a SMAPE of ~~52.5~~38% between estimated and reported volumes for ~~238~~ 494 lakes in the USA, South Africa, India, Spain and Australia. In situ bathymetric measurements would be ~~ideal~~ needed to more ~~precisely~~ accurately estimate total lake volume, but they are not available for the majority of the millions of lakes globally. Relative lake volume storage changes ~~could be calculated~~were measured for lakes where their satellite-derived extents and heights were both available. The ~~average~~ median correlation between our relative storage product and ~~a~~ previous MODIS-derived data was ~~0.90~~0.94.

~~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.~~ In addition, we investigated where and for how many lakes whose NRT storage time series can be estimated by remote sensing around the world. The results indicated that the most suitable ~~places~~ regions for satellite-based ~~to enable~~ lake monitoring ~~capabilities~~ include ~~is~~ the USA, southeastern South America, the Mediterranean, southern Africa, southern Asia, and Australia. ~~The~~ NRT monitoring ~~abilities were then~~ was achieved using BLUEDOT (Sentinel-2), ICESat-2 and GREALM~~ in this study~~. The validation results showed that the performance of NRT storage estimat~~es~~ion decreases slightly compared to historical ~~storage~~ estimates~~,~~ but ~~it~~ are still of good quality~~does not systematically occur in our datasets~~. In the future, the estimates ~~GloLakes can~~ could ~~be potentially~~ be improved using Sentinel-2~~-~~-derived global surface water mapping and observations from the recently launched SWOT mission.

Author contribution. JH and AIJMVD conceived the idea. JH developed the methodology and software, carried out the investigation, curated the data and wrote the first manuscript draft. 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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