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A novel remote sensing method to estimate pixel-wise lake water depth using dynamic water-land boundary and lakebed topography

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ABSTRACT
Water depth, a fundamental characteristic of a lake, is important for understanding climatic, ecological, and hydrological processes. However, lake water depth data are still scarce due to the high cost of in-situ measurements and the limitations of remote sensing observations. In this study, a novel method was developed to estimate time series of pixel-wise water depths of lakes that have ever exposed their bottom by remote sensing observations. Lake water depths were calculated as the difference between the elevations of the dynamic water surface and the historical lakebed elevations using optical images and DEM data. The method was applied in the Sahel-Sudano-Guinean region of Africa where complex climatic conditions and rare in-situ measurements. Experiments showed that the proposed method could get consistent water depths compared with the HydroLAKES data, i.e. with a MAE of 0.86 m and a RMSE of 1.69 m, and water surface elevations similar to the estimates derived from ICESat/ICESat-2 measurements with a MAE of 3.79 m and a RMSE of 5.92 m. The method can provide pixel-wise information on lake water depth at high temporal frequency, and is expected to provide an efficient solution to gather essential information on lakes.

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Lake water depth; water-land boundary; land surface water; water surface elevation

1. Introduction

Lakes are one of the most important sources of freshwater, with more than 80% of liquid freshwater stored in inland lakes, although global lake area accounts for only ∼4% of the total land area (Allen and Pavelsky 2018; Woolway et al. 2020; Yigzaw et al. 2018). Accumulating evidence documents the large spatiotemporal variability in lake area, water level and volume under the influence of climatic variability and increased human activities in recent decades (Feng et al. 2022; Luo et al. 2022; Verpoorter et al. 2014; Woolway et al. 2020). Among the intrinsic properties of lakes, water depth plays

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a critical role because it determines lake water volume and heat storage (Zhao and Gao 2019; Zhao, Gao, and Cai 2020), water chemical composition (Sobek 2011), zooplankton dynamics (Obertegger et al. 2007), etc. However, measurements of lake water depth are still insufficient, which remains a major challenge for lake water balance assessment and management (Liu et al. 2022).

Satellite observations have been widely used for lake monitoring, especially in ungauged basins, with many advantages over traditional station-based measurements such as hydrological stations, shipborne sonar, single- or multi-beam echosounders, and airborne sounders, e.g. low cost, high efficiency, large spatial coverage, etc. (Xie et al. 2022; Zhan et al. 2022). Datasets on global water surface extent have been generated by using optical remote sensing (Pekel et al. 2016; Pickens et al. 2020; Yamazaki, Trigg, and Ikeshima 2015), though the spatial gaps caused by the unavoidable cloud contaminations still exist in some land surface water products (Huang et al. 2018; Ogilvie et al. 2018). Retrieving water depth is much more challenging and it requires the knowledge of the underlying topography, which is only available for a small subset of the world's lakes and reservoirs due to the high cost of in-situ measurements (Alsdorf, Rodríguez, and Lettenmaier 2007; Peng et al. 2006; Weekley and Li 2021).

To overcome the shortcomings of remote sensing observations, the combination of measured data and remote sensing observations has been applied to estimate water depth. The researches (Li et al. 2021; Ma et al. 2020; Mateo-Pérez et al. 2020; Tsolakidis and Vafiadis 2019; Yang et al. 2022) have established relationships between the multi-spectral water-leaving radiance and measured lake water depths to estimate the unknown water depth. Nevertheless, methods based on such measurements are limited to a lake depth less than 30 m say (Mateo-Pérez et al. 2020; Yang et al. 2022). This is related to the penetration depth of sunlight, i.e. 50–70 m in the blue band, 30–40 m in the green band, less than 10 m in red band, and less than 1 m in near-infrared band. The water-leaving radiance is affected by suspended matter, water color, and transparency. In addition, geo-statistical models have been developed and widely used to estimate lake water depth using a generic area-depth relationship (Hakanson and Peters 1995; Håkanson and Karlsson 1984). These methods are further improved by introducing additional predictor variables of the surface topography in the area surrounding the lake to estimate the bathymetry (Cael, Heathcote, and Seekell 2017; Delaney et al. 2022; Haakanson and Peters 1995; Heathcote et al. 2015; Hollister, Milstead, and Urrutia 2011; Sobek 2011). These additional predictor variables include the lake buffer topography variable, e.g. the elevation range of lake surroundings (Haakanson and Peters 1995; Hollister, Milstead, and Urrutia 2011; Sobek 2011), topographic slope (Heathcote et al. 2015; Messager et al. 2016), and the Hurst coefficient (Cael, Heathcote, and Seekell 2017) evaluated in the vicinity of the land-water boundary. For example, using 12,150 in-situ measurements as samples, the widely used HydroLAKES data has been produced by constructing a geo-statistical model including lake area and the topographical characteristics around each lake. Geostatistical models are elegant in their solid theoretical foundation, interpretability, and ease of implementation. It is noted that their ability to predict the lake water depth is highly dependent on in-situ measurements as training samples. Most of the available field measurements are located in Europe and the Americas. Model performance becomes uncertain in regions without adequate in-situ water depth measurements. Nevertheless, the HydroLAKES is still the only available dataset providing the water depth for global lakes and is widely used (Yao et al. 2023; Zhao et al. 2022).

With the operation of the Ice, Cloud and land Elevation Satellite Geoscience Laser Altimeter System (ICESat/GLAS) and ICESat-2 Advanced Topographic Laser Altimeter System (ICESat-2/ATLAS) the wealth of surface elevation observations thus obtained are used for monitoring lake changes. The observations by ICESat/GLAS and ICESat-2/ATLAS (ICESat/ICESat-2 in short) capture the absolute water surface elevation rather than the absolute water depth and have been used to determine the lake water level to estimate changes in lake water volume (Han et al. 2024; Shen, Jia, and Ren 2022; Xu et al. 2021). Moreover, the water surface elevations measured by ICESat/ICESat-2 are also considered as an indirect approach to estimate the water depth. Literature documents how the area-elevation relationship can be constructed using lake extent and lake water surface elevation to estimate the lakebed elevation and the absolute water depth (Armon et al. 2020; Li et al. 2020; Liu et al. 2022). Empirical formulas, e.g. linear model, power function, and machine learning methods are built to link the lake area and water surface elevation (Qi et al. 2022; Yang et al. 2022). However, the spatially sparse observations by ICESat/ICESat-2 may not be sufficient to establish a reliable area-elevation relationship for all global lakes (Feng et al. 2022; Luo et al. 2022), i.e. inadequate or missing observations over small and seasonal lakes may be not enough to support a reliable relationship. Some authors attempt to combine multi-spectral images and ICESat/ICESat-2 measurements to derive the underwater topography of desert and coastal lakes (Armon et al. 2020; Xu et al. 2022). They determined a relationship between water occurrence percentages, i.e. the pixel-wise relative frequency of water, and water surface elevations generated by ICESat/ICESat-2, then inferred the entire lake surface elevation. Unfortunately, this approach is feasible only for desert and coastal lakes with dramatic changes of surface elevation. Other approaches capture the dynamic water surface elevations and lake area (or water occurrence percentages) and build a relationship between them. These relationships provide estimations of the water depth given observations of the lake area (or water occurrence percentages), which requires sufficient observations. Moreover, the above statistical methods based on correlations usually provide generalized statistics, e.g. the mean water depth, rather than the spatial distribution of water depth within the lake extent, which is still a challenge to be addressed. Other researches have predicted and estimated the underwater topographic slopes by extrapolating the terrain slopes adjacent to lakes, thereby estimating the water depth (Fang et al. 2023; Liu and Song 2022). The latest research Liu et al. (2024) completed a quasi-global investigation of the Shuttle Radar Topography Mission (SRTM) Digital Elevation Model (DEM) regarding its capability of estimating the inundated-area bathymetry and evaluating the feasibility of mapping the water depth of inundated-lakes. This study suggests that mapping the underwater topography of lakes with the aid of DEMs is valuable for estimating the water depth of global lakes.

In summary, although the existing methods can partially solve the problem of water depth estimation, it still appears that available estimates of lake water depth share two main limitations: (a) the absence of in-situ measurements of water depth and (b) the over-generalized estimation of water depth. This study describes a novel method to estimate dynamic lake water depth, which provides the spatiotemporal distribution of the lake water depth, rather than the mean or maximum value of lake water depth at a given moment in time. The results are compared with the estimations of water surface elevation and water depth based on ICESat/GLAS and ICESat-2/ATLAS observations and the existing lake dataset, HydroLAKES. The uncertainties of the method are also discussed and analyzed. Since the characteristics of lakes and reservoirs in remote sensing multi-spectral image data are similar, both natural lakes and man-made reservoirs are considered as lakes and the differences between these two types of water bodies are not discussed in this study.

2. Study area and datasets

The study area covers the Sahel-Sudano-Guinean region of Africa within the boundaries of 0–25°N and 20°W–60°E (Figure 1). The study area is an ecological and climatic transition zone characterized by a steep rainfall gradient from ∼100 mm/year in the Sahel region to more than 2000 mm/year in the Guinean region to the south (Asenso Barnieh et al. 2022; Zhou et al. 2021). Three of Africa's largest rivers, the Nile, the Congo and the Niger flow through the study area. There are more than 2000 lakes distributed in the study area. Spatial and inter-annual variability of rainfall leads to a large variability in lake extent and conditions (Ramillien, Frappart, and Seoane 2014). The scarcity of in-situ measurements pertaining to lake bathymetry within the study area persists, hindered by multiple factors.

The datasets used in the study include the surface water maps, i.e. the monthly Joint Research Centre's Global Surface Water Dataset (JRC GSWD) and the 8-day Global Surface Water Extent Dataset (GSWED), the Global River Widths from Landsat Database (GRWL), the 'Bare-Earth'

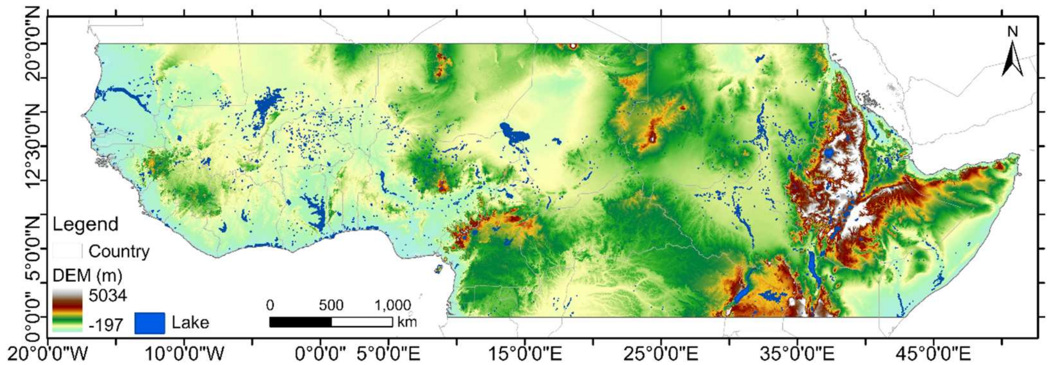

Figure 1. The lake extents and terrain elevation (SRTM DEM in February 2000) in the study area.

SRTM DEM, HydroLAKES, ICESat/ICESat-2. The key details of the datasets are listed in Table 1 and further details on these datasets are provided in Supplementary A.

3. Method

The core idea of the proposed method is to estimate the pixel-wise lake water depth as the difference between the elevation of the dynamic water surface and the lakebed topography (Figure 2). This method relies on two assumptions: (1) the lakebed topography can be fully observed at a given time, and (2) the lakebed topography has not changed significantly over time. The first assumption provides the theoretical basis to use the underwater topography to estimate lake water depth. The second one avoids considering changes in the lakebed topography over time. The method focuses on those lakes that were dry at the time of the SRTM DEM acquisition in February 2000 (those lakes meeting this condition will be referred to as 'dry lakes'). The pixel-wise elevations of the lakebed of dry lakes are extracted from the SRTM DEM, while the dynamic water surface elevation is estimated from the elevations along the water-land boundary when the lake was inundated, i.e. assuming that the water surface is approximately horizontal (Figure 2).

The method work-flow includes four main steps (Figure 3). First, monthly maps of lake extent are produced by combining the datasets of surface water and rivers (Supplementary B). Next, dry lakes in February 2000, i.e. at the time of the SRTM DEM acquisition, are extracted. The dynamic water surface elevations are calculated using the water-land boundary and DEM. Then, the pixel-wise spatial distribution of water depth in the selected dry lakes is calculated as the difference between the dynamic lake surface elevation and the bed elevation within each lake extent. Finally, the estimated water surface elevation and depth are evaluated by using HydroLAKES and ICESat/ICESat-2 data as references. The pre-processing of ICESat/ICESat-2 and the performance metrics

Table 1. Key details of the datasets used in the study.

Dataset	Spatial resolution	Temporal coverage	Source
Joint Research Centre's Global Surface Water Dataset (JRC GSWD)	30 m	2000–2020	Joint Research Centre
Global Surface Water Extent Dataset (GSWED)	250 m	2000–2020	International Research Center of Big Data for Sustainable Development Goals
Global River Widths from Landsat Database (GRWL)	/	/	Allen and Pavelsky (2018)
'Bare-Earth' SRTM DEM	90 m	February 2000	O'Loughlin et al. (2016)
HydroLAKES	/	/	HydroSHEDS of World Wildlife Fund
ICESat/GLAS and ICESat-2/ATLAS	/	2003–2009 2018–2020	NASA National Snow and Ice Data Center

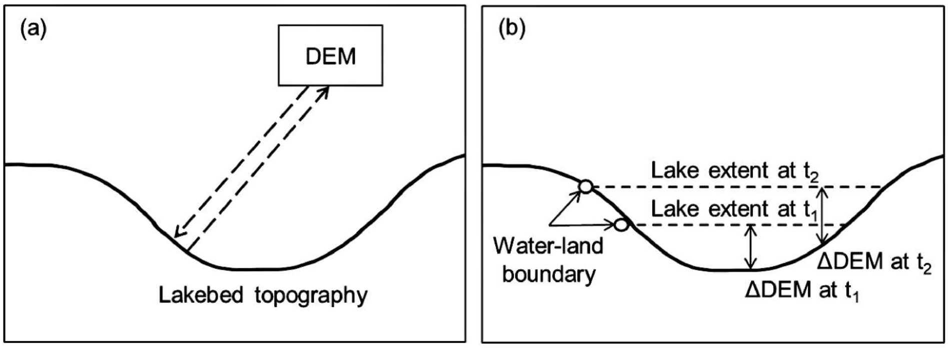

Figure 2. Conceptual illustration of the proposed method. (a) The lakebed elevations, if exposed, can be completely determined using a DEM; (b) the elevations along water-land boundary at time t_1 and t_2 are determined using the same DEM to estimate the elevation of the water surface.

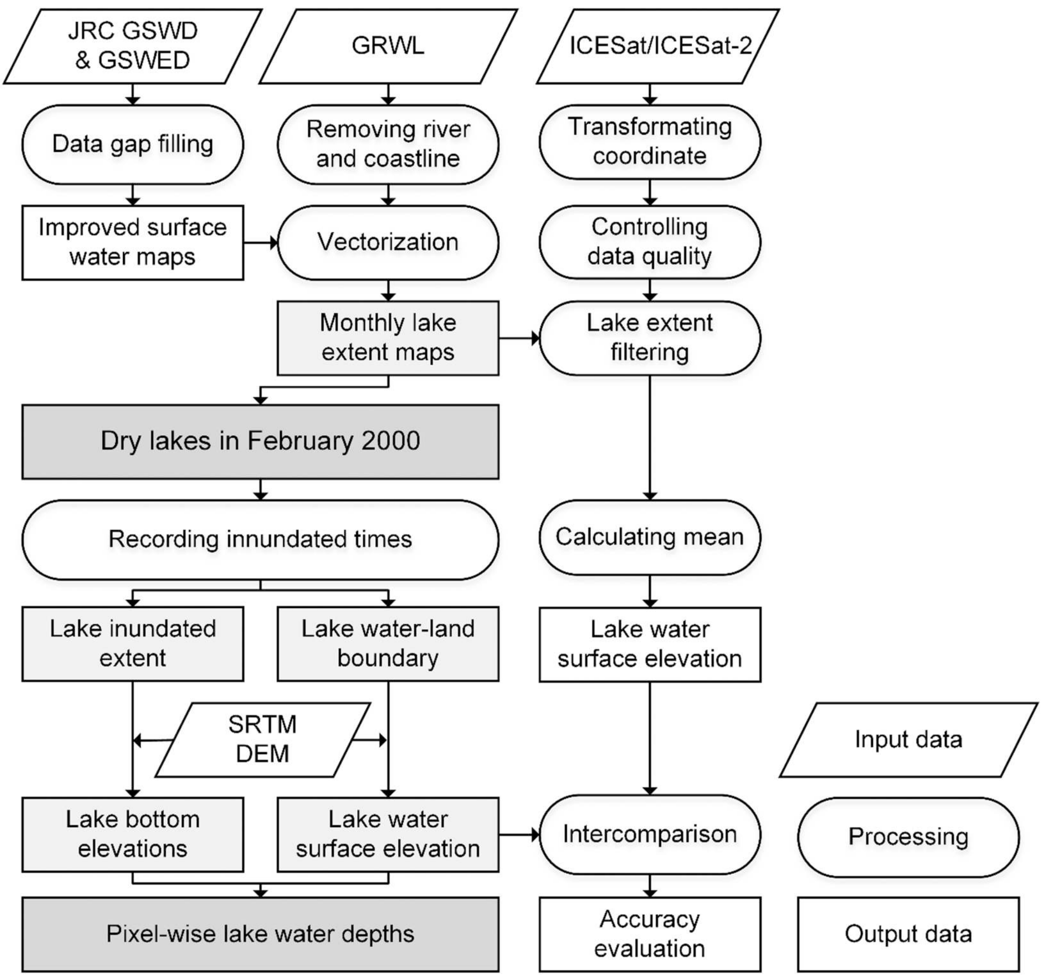

Figure 3. The workflow of the procedure to estimate dynamic lake water depth.

are described in Supplementary C and D. The Geospatial Data Abstraction Library (GDAL) in Python and ArcGIS software are applied in our data processing.

3.1. Estimation of dynamic water surface elevations

Dry lakes (i.e. fully exposed lakebeds) in February 2000, i.e. the time of the SRTM DEM acquisition, are identified by comparing the lake extent images in February 2000 with those in other months of years after February 2000. The elevations of the lakebed topography of these dry lakes in February 2000 are determined from the SRTM DEM, and further used in combination with the vectorized monthly lake extent maps to estimate the monthly elevation of the lake water surface for the months between March 2000 and December 2020, when water appeared after February 2000, according to the following procedure: (a) the water-land boundary line of a lake is determined in the monthly lake water extent image; (b) a 30 m buffer zone is defined on both sides of the water-land boundary line of a lake (Figure 4); (c) mean and standard deviation values of SRTM DEM elevations along the water-land boundary within the buffer zone are calculated using the 'Zonal Statistics as Table' tool which is a tool summarizing the values of a raster within the zones of another dataset and reporting the statistical results as a table in ArcGIS; (d) the mean elevation along the buffered water-land boundary is used as an estimate of the monthly lake water surface elevation to determine the monthly water depth, which would partially filter out the errors. This ensured that elevations on both sides of the water-land boundary are sampled to the equal extents. In an ideal situation, the standard deviation should be zero because the water-land boundary elevation should be the same everywhere, but in practice, the impact of spatial resolution and errors in the water-land boundary elevation data and the water extent data can result in significant differences.

The lakes with the large elevation differences at water-land boundary, i.e. maximum monthly standard deviation of the boundary elevations greater than 40 m and mean monthly standard deviation greater than 20 m, are detected and removed to avoid misclassification of water on the surface water maps. The elevations of the actual water-land boundary of a lake should be similar because the lake water surface is usually horizontal. If the temporal changes of the lake surface elevation and its variabilities along the boundary are too large, a likely explanation is the misclassification of the land-water boundary. For example, there are several cases in Ethiopia where boundaries have large variability in elevation. After inspection, we recognize them in Google Earth as being volcanic rocks but misclassified as water in the GSWED.

3.2. Estimation of lake water depths

Monthly lake water surface elevations maps are generated as described in Section 3.1. The pixel-wise monthly lake water depths from March 2000 to December 2020 are calculated as the difference between the monthly lake water surface elevation and the lakebed elevations in February 2000, i.e.

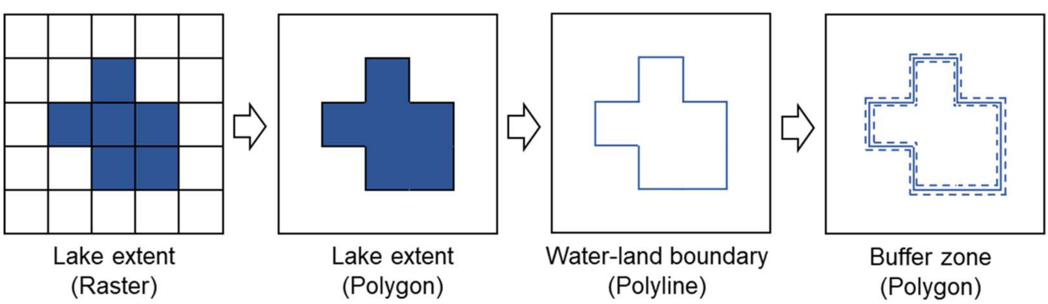

Figure 4. The vectorization of the water-land boundary.

when the lakes were dry:

$$Water\ depth_{i,j,m} = Elevation_{i,j,m}^{water\ surface} - Elevation_{i,j}^{lakebed} \tag{1}$$

$$Elevation_{i,j,m}^{water\ surface} = mean(Elevation_{m}^{water-land\ boundary}) \tag{2}$$

$$Elevation_{i,j}^{lakebed} = Elevation_{i,j,\ Feb2000} \tag{3}$$

where $Water\ depth_{i,j,m}$ is the lake water depth at the pixel (i, j) in month m; $Elevation_{i,j,m}^{water\ surface}$ and $Elevation_{m}^{water-land\ boundary}$ are the elevations of the lake water surface at the pixel (i, j) and the water-land boundary in month m, respectively; $Elevation_{i,j}^{lakebed}$ and $Elevation_{i,j,\ Feb2000}$ are the lakebed elevations at the pixel (i, j) in February 2000 derived from the SRTM DEM. In addition, the mean, maximum and standard deviation of the lake water depths are estimated to spatially characterize the lake bathymetry.

4. Result and analysis

4.1. Dry lakes in February 2000

The maps of lake extent included 2258 lakes in the Sahel-Sudan-Guinea region of Africa in the period 2000–2020. Over half of these lakes, i.e. 1235 out of 2258, were dry in February 2000, i.e. the elevation of the bed could be mapped using the SRTM DEM. In addition, 42 of the 1235 dry lakes were measured 68 times by ICESat/ICESat-2 data when these lakes were filled with water. 99 dry lakes, along with their mean water depth, were included in the HydroLAKES data. From 2000 to 2020, the lakes in the study area evolved in response to progressively wetter conditions and to the construction of water projects, leading to an increase in the number of lakes. February falls in the dry season in this region, thus explaining the large number of dry lakes captured by the SRTM DEM in February 2000. There were more lakes located in the eastern and western area of the region, while few lakes were located in the central region (Figure 5). The spatial distribution of lakes which were dry in February 2000 was similar as the spatial distribution of all lakes.

Two lakes were analyzed in detail as examples of the monthly lake extent results (Figures 6 and 7). The selected dry lakes were newly built reservoirs during 2000–2020 and could be observed across the stages from dry to inundated. The positions of the two lakes were shown in Supplementary Figure 1. The Bui Reservoir in Ghana (Figure 6) was constructed between 2007 and 2013 (buipower.com). The lake boundaries in February 2000, 2012, and March 2014 were shown on the

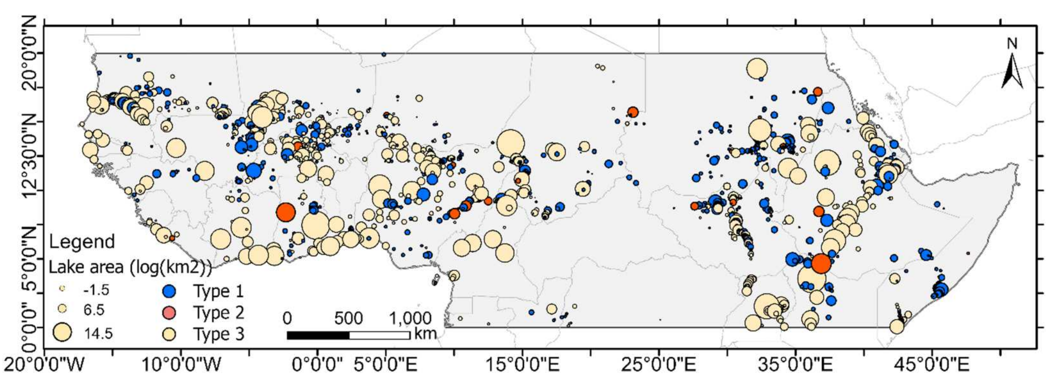

Figure 5. Location map of the lakes in the study area of the Sahel-Sudan-Guinea region of Africa discovered by the lake extent datasets. Three types of lakes were considered: Type 1 (blue circles) includes 1193 dry lakes in February 2000, which were never measured by ICESat and ICESat-2. Type 2 (orange circles) includes 42 dry lakes in February 2000 and measured by ICESat and ICESat-2. Type 3 (yellow points) includes 1023 lakes that were inundated in February 2000.

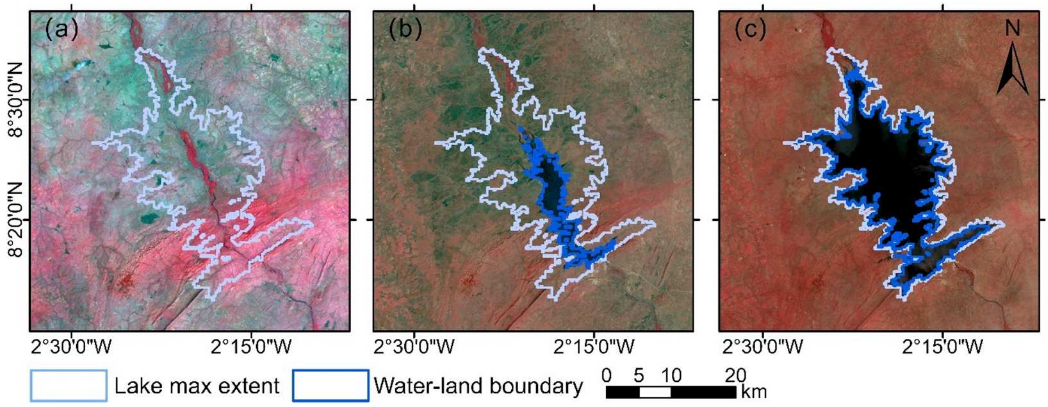

Figure 6. The lake extent maps of Bui Reservoir in Ghana in (a) February 2000, (b) February 2012, and (c) March 2014.

Landsat-based maps with standard false color display. The Samendeni reservoir (Figure 7), the third largest reservoir in Burkina Faso, was dammed in 2017 and inaugurated in 2019 (www.icafrica.org/en/news-events/infrastructure-news/article/burkina-faso-samendeni-hydroelectric-dam-officially-operational-in-bama-672632). The lake boundaries changed during the construction of the reservoirs, as shown by the Landsat-based maps (Figures 6 and 7). The lakebed topography was exposed and could be easily and completely obtained from the SRTM DEM data prior to the project completion. The monthly lake extent maps captured the temporal variability of the lake extent and provided the corresponding lake boundaries. This dynamic information helped us to estimate the lake water depth at any given time.

4.2. Time series of estimated pixel-wise lake water depth

The dry lakes in February 2000 included the lakes that had never been inundated before 2000 and seasonally dry lakes. Many of the seasonally dry lakes were filling with the onset of the rainy season after February 2000. Among the 1235 dry lakes in February 2000, there were 648 lakes inundated in 2005, 900 in 2010, 972 in 2015, and 1074 in 2020, respectively (Supplementary Figure 2). The spatial and frequency distributions of the estimated water depths for the dry lakes (Figure 8) showed that the mean lake water depths were concentrated in the range 0–10 m with maximum value of ~22

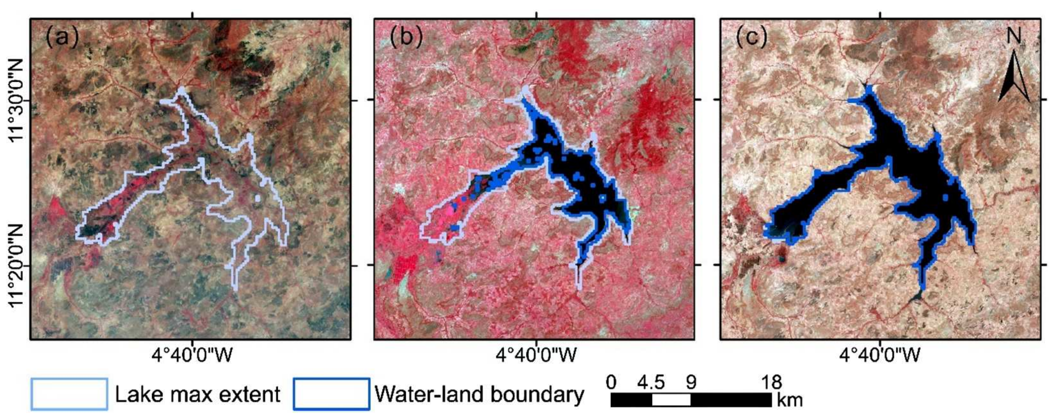

Figure 7. The lake extent maps of Samendeni Reservoir in Burkina Faso in (a) February 2000, (b) October 2017, and (c) January 2020.

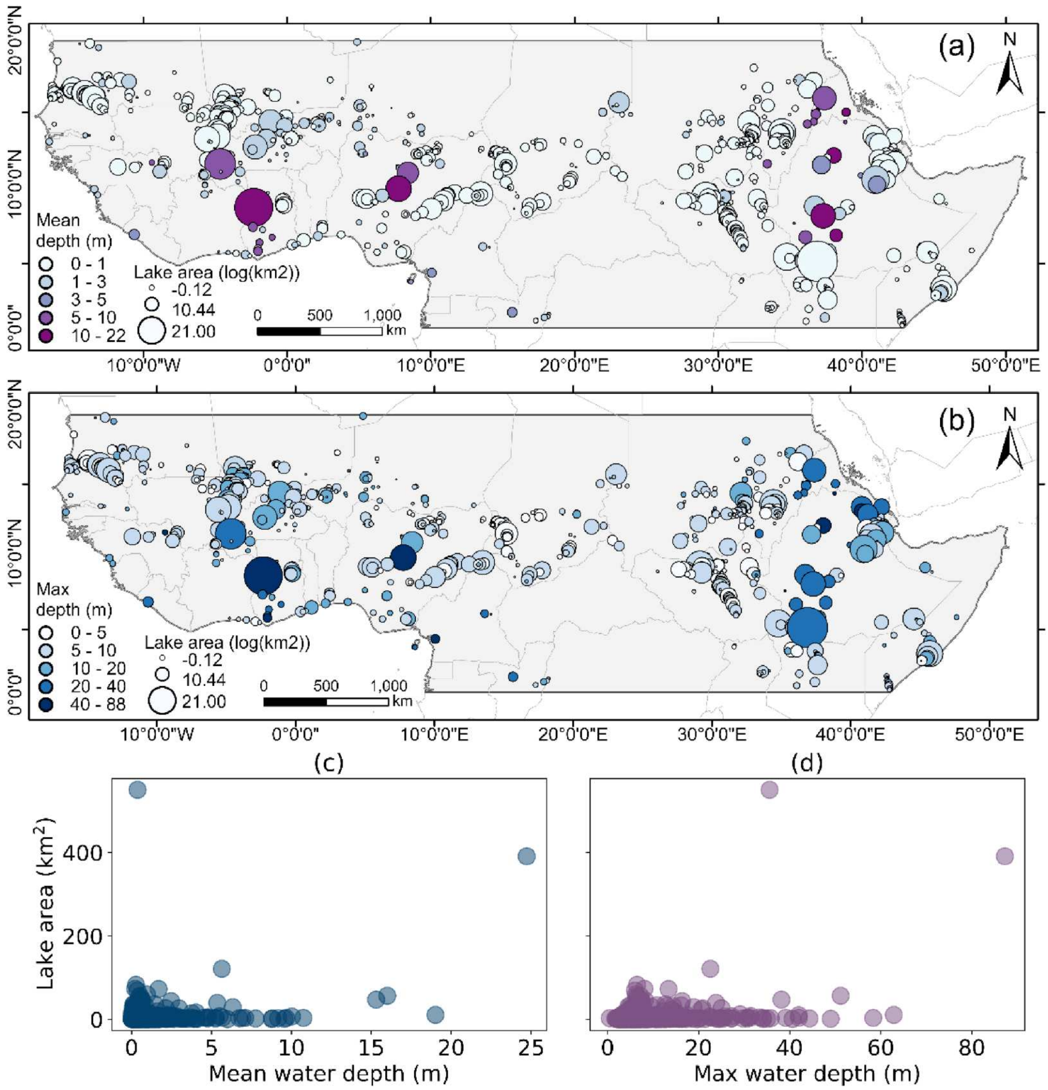

Figure 8. The estimated (a) mean and (b) max water depths and the histograms of the (c) mean and (d) max water depths for the dry lakes during 2000–2020 in the study area.

m. The deepest water depths were in the range of 0–40 m with a maximum value of ~88 m. Shallow lakes dominated the relatively flat western region, while deeper lakes were found in the rugged eastern region. Although most dry lakes in the study area were shallow lakes, some lakes reached significantly deeper depth. There were 563 newly inundated lakes in 2000 compared with the inundated lakes in February 2000, and new lakes achieved the maximum number of 265 in October 2000, which meant that about one-third of the newly appearing lakes were seasonally dry in 2000 (Figure 9). The number of new lakes (including seasonal lakes) had increased each year, and the depth of the lakes had increased from 2000 to 2020 (Figure 9). August to October each year was the period when newly inundated lakes occurred most intensively during 2000–2020.

The Bui and Samendeni reservoirs were studied in more detail to illustrate the features of the dataset on lake water depth derived in this study (Figures 10 and 11). Deeper water depths during 2013–2020 (Figure 10a) for Bui reservoirs and during 2018–2020 (Figure 10a) for Samendeni lake were found mainly due to the completion of the two dams in 2013 (Bui) and 2018 (Samendeni),

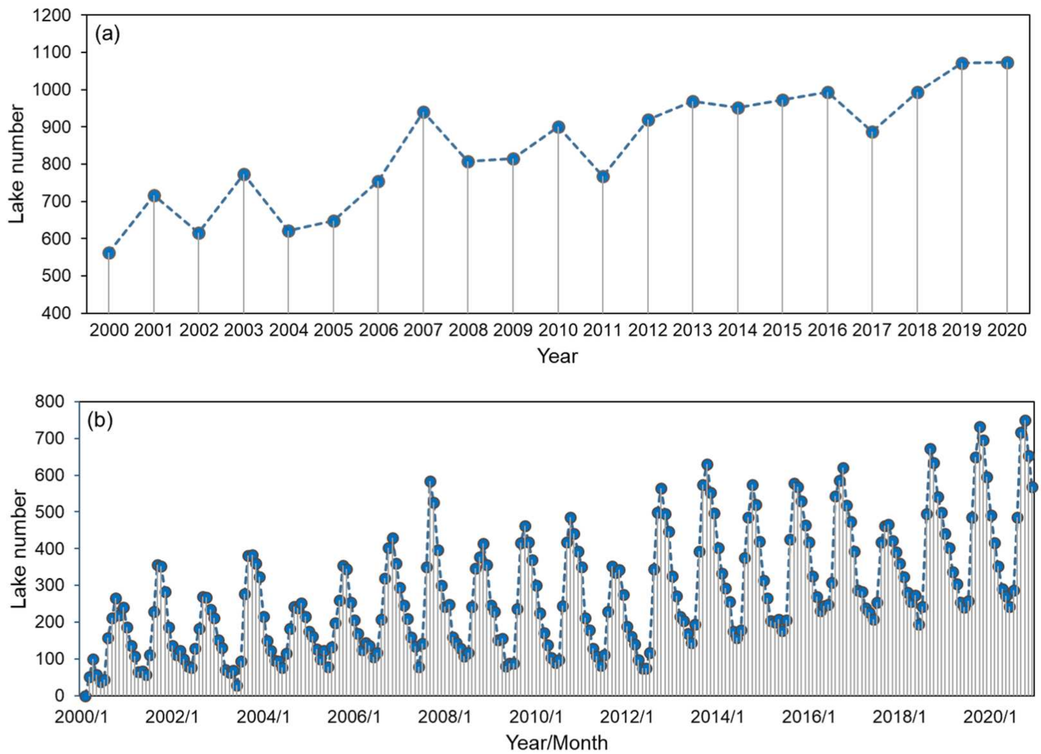

Figure 9. The (a) annual and (b) monthly number of newly inundated lakes compared to the baseline (February 2000) during 2000–2021 in the study area.

respectively. The three subgraphs (Figures 10 and 11b–d) clearly showed the different periods of the lakes during expansion and for two different periods after construction. The spatiotemporal distribution of water depths in these two lakes under water-filled conditions demonstrated the method feasibility to estimate water depths. After the completion of the reservoirs, seasonal variations in lake water depth were more pronounced and regular than before completion of the dam, and followed the seasonal variation of the lake extent. According to our estimations, the annual mean water depths of the Bui reservoir from 2014 to 2020 were 21.1 ± 5.7 m, 19.0 ± 8.9 m, 22.5 ± 7.0 m, 22.7 ± 4.8 m, 24.7 ± 5.0 m, 22.2 ± 7.7 m, and 21.3 ± 8.9 m (mean ± Std), respectively. The maximum monthly water depths of Bui reservoir in each year during 2014–2020 were 81.9, 85.43, 85.8, 82.3, 85.4, 86.5 and 87.2 m, respectively. These results were close to the values of a designed maximum water depth of about 88 m and an average water depth of 29 m for the Bui reservoir reported by the Environmental Resources Management of Ghana before the dam was completed (web.archive.org/web/20120308215626/http://www.dialoguebarrages.org/dialoguebarrages/images/downloads/Final_ESIA_Bui_HEP_Final_report.pdf). The maximum values (28.1, 30.0, 30.4, 28.5, 29.8, 30.0, and 30.8 m during 2014–2020) of the estimated yearly average water depths were closer to the reported mean water depth.

4.3. Accuracy evaluation

Since in-situ measurements of lake water depth were not available in the study area, we evaluated the accuracy of our estimates against the HydroLAKES data and the observations from ICESat/ICESat2. In this evaluation, we used multiple metrics (Chai and Draxler 2014; Hyndman and Koehler 2006; Tofallis 2017), i.e. Bias, MAE, RMSE, SMAPE, and R^2 described in Supplementary D.

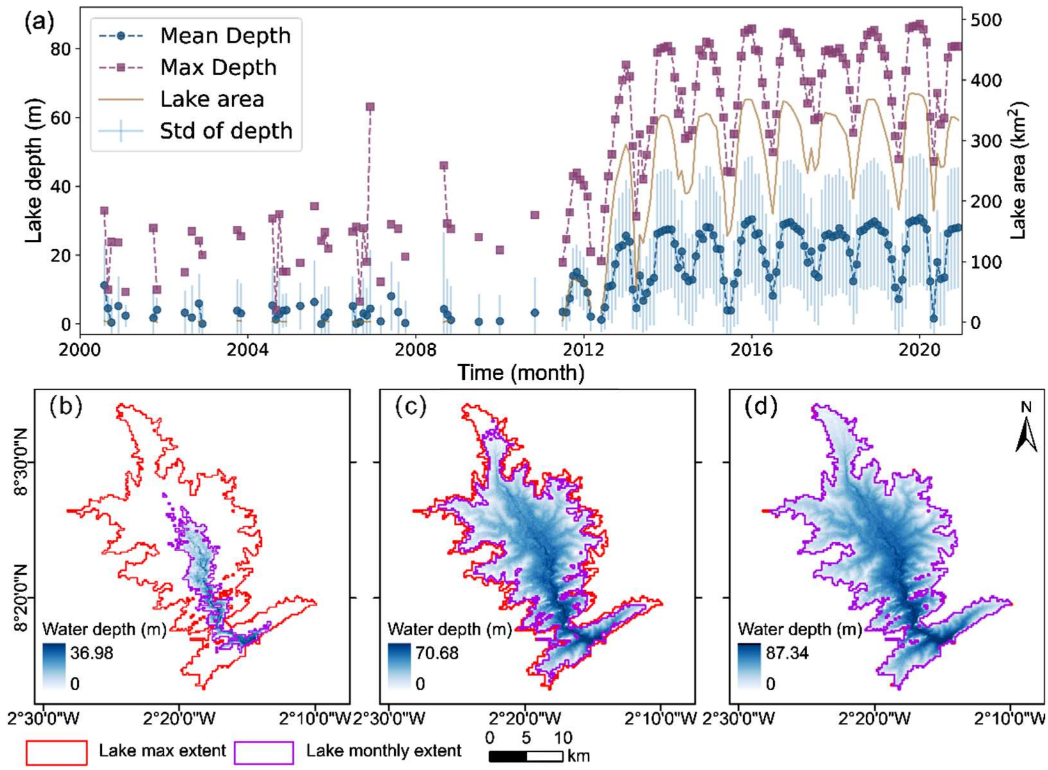

Figure 10. Bui Reservoir: (a) monthly time series of lake water depth during 2000–2020, and spatial distributions of lake water depth in (b) February 2012, (c) March 2014, and (d) January 2020.

4.3.1. Comparison with the available lake water depth data

The study compared our estimations of the mean lake water depth with the HydroLAKES data on 99 dry lakes (Figure 12a). We also compared our estimates of the mean lake surface elevation with the HydroLAKES data on the same 99 dry lakes (Figure 12b). Our estimates of the lake surface elevation were compared with the elevation obtained by adding up the mean elevation of the lakebed obtained from the SRTM DEM in February 2000 to the mean water depth of HydroLAKES. The results of the water depth comparison were: Bias = −0.78 m, MAE = 0.86 m, RMSE = 1.69 m, SMAPE = 52.68%, and R^2 = 0.7288. On the other hand, the results of comparing the lake surface elevation were: Bias = −1.58 m, MAE = 1.58 m, RMSE = 2.66 m, SMAPE = 8.31%, and R^2 = 0.9999. Good agreement in mean water depth was found between the two datasets. The RMSEs larger than MAEs meant that our estimates included abnormal values on some lakes. Furthermore, we compared the max and mean estimated water depth with the HydroLAKES mean water depth dataset for the eight deepest lakes (Supplementary E Figure 3). This comparison revealed that our estimates of the mean water depths were systematically lower than the HydroLAKES data. Conversely, our estimates of the water surface elevations were systematically higher than the HydroLAKES data. Our method captured the intra- and interannual variability of water depth rather than the long-term averages provided by HydroLAKES. The reasons causing the difference are discussed in Section 5.

4.3.2. Comparison with the water surface elevations and depths retrieved with ICESat/ICESat-2 data

ICESat/ICESat-2 directly observed the elevations of the lake water surface, but not the water depth. The estimation of the lake surface elevation using the water-land boundary information was a key aspect of our method and largely determined the accuracy of the water depth estimations. We

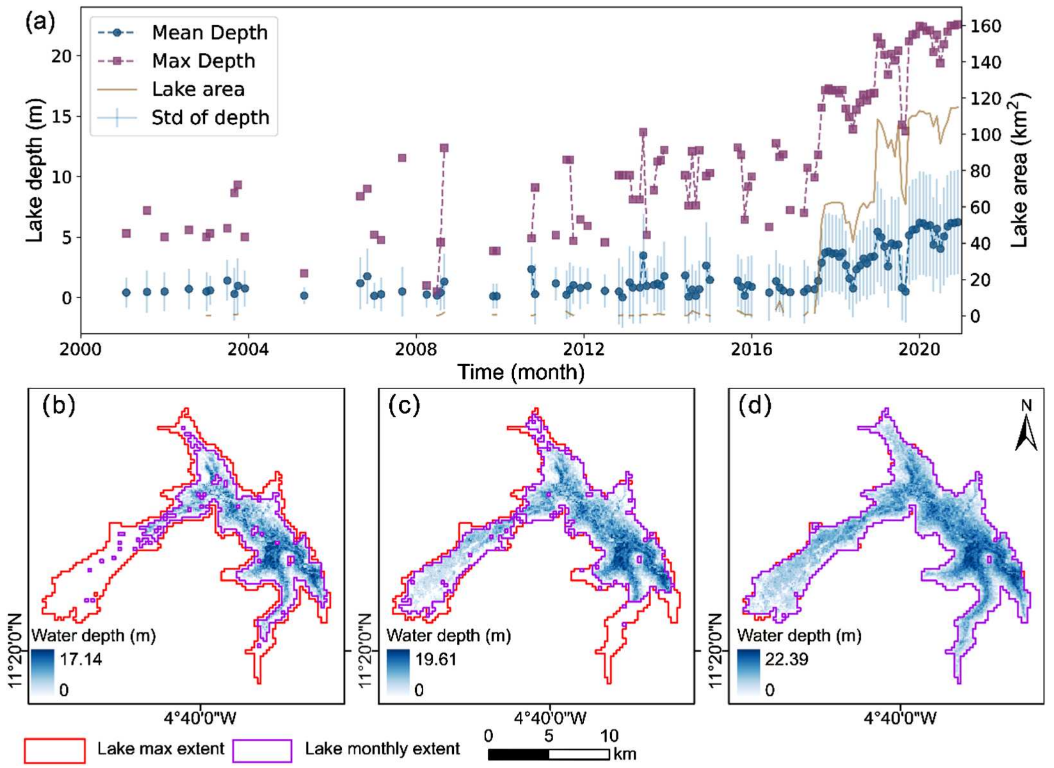

Figure 11. Bui Reservoir: (a) monthly time series of lake water depth during 2000–2020, and spatial distributions of lake water depth in (b) October 2017, (c) June 2019, and (d) January 2020.

compared the mean water surface elevations estimated by our method and the ICESat/ICESat-2 observations. The estimated water depth under the footprints of ICESat/ICESat-2 laser beams were extracted and compared with our estimates (described in Supplementary C). There were 68 observations of 42 dry lakes (Figure 13 and Table 2). These samples and lakes were ones that had their bottom elevations exposed in February 2000 and were also observed when inundated

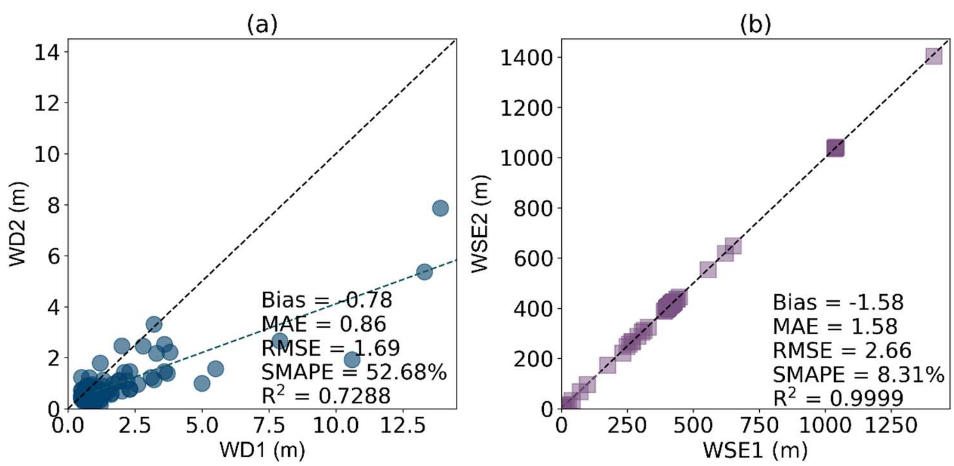

Figure 12. Comparison of our estimates with the HydroLAKES data: (a) mean water depth WD1: HydroLAKES; WD2: our estimates and (b) mean water surface elevation. WSE1: HydroLAKES; WSE2: our estimates.

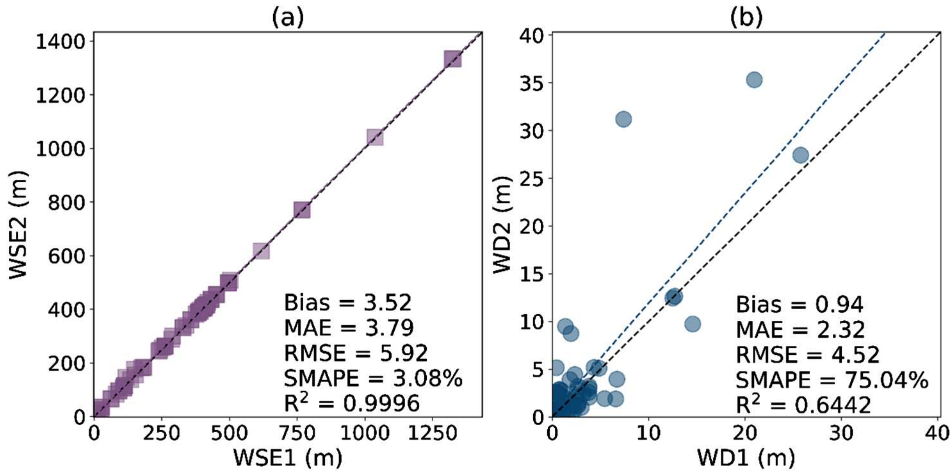

Figure 13. Comparison of our estimations with the ICESat/ICESat-2 observations: (a) water surface elevation, WSE1: ICESat/ICESat-2; WSE2: our estimations and (b) estimated water depth under the footprint, WD1: ICESat/ICESat-2; WD2: our estimations.

by the ICESat/ICESat-2. In addition, we extracted at random 34 out of the 68 available ICESat/ICESat-2 observations and repeated the evaluation 5 times (Supplementary E Table 2). The additional evaluation helped us to better understand the performances of the proposed method.

As regards the water surface elevations, the values of the error metrics were: Bias = 2.21 m (ICESat/GLAS), 5.91 m (ICESat-2/ATLAS), and 3.52 m (Total), MAE = 2.76 m (ICESat/GLAS), 6.24 m (ICESat-2/ATLAS), and 4.02 m (Total) RMSE = 3.13 m (ICESat/GLAS), 9.45 m (ICESat-2/ATLAS), and 6.20 m (Total). The deviations of the results by our method from ICESat-2/ATLAS were greater than those from ICESat/GLAS. Our estimates of water surface elevation had a satisfactory relative error (SMPAE = 3.08%) and high R^2 with 0.9996. As regards the estimated water depths, the metrics gave: Bias = −0.26 m (ICESat/GLAS), 1.36 (ICESat-2/ATLAS), and 1.68 (Total), MAE = 2.21 m (ICESat/GLAS), 3.24 m (ICESat-2/ATLAS), and 2.32 m (Total) RMSE = 1.68 m (ICESat/GLAS), 6.10 m (ICESat-2/ATLAS), and 4.52 m (Total). Our estimated water depths were also rather similar to the reference ICESat measurements. The relative error (SMPAE = 75.04% and R^2 = 0.6442 in total) indicated a good agreement of our estimates with the reference data. Similar to the results of the HydroLAKES evaluation, the MAEs values were satisfactory, while the RMSEs were larger. This indicated that over all our estimates were fine but errors were larger for individual lakes. The estimates of water surface elevation were better than water depth. The lakes on plateaus or mountains had large water surface elevations, thereby leading to small relative errors (SMAPE). The additional evaluations (Supplementary Table 2) confirmed these finding.

4.4. Uncertainty of estimated water surface elevation

Ideally, the lake water surface was horizontal and the elevations were equal everywhere along a lake boundary. The water-land boundaries were continuous linear features, but in raster images the

Table 2. The evaluated metrics of ICESat/ICESat-2.

	Sensor	Bias (m)	MAE (m)	RMSE (m)	SMAPE (%)	R^2
Water surface elevation	ICESat	2.21	2.60	2.94	2.34	0.9999
	ICESat-2	5.91	5.94	9.11	4.42	0.9996
	Total	3.52	3.79	5.92	3.08	0.9996
Water depth	ICESat	−0.26	1.36	1.68	81.85	0.6442
	ICESat-2	2.10	3.24	6.10	68.49	0.6352
	Total	0.94	2.32	4.52	75.04	0.6442

boundaries were sampled at the spatial resolution of the raster. There is an unavoidable bias between the estimated boundaries and the real contour lines that affects the accuracy of the estimated water surface elevation, making a full evaluation of the impact of spatial resolution necessary.

4.4.1. Standard error of estimated water-land boundary elevations

The study evaluated the extracted water-land boundary elevations using the standard error (Ste) calculated when the exposed lake was inundated (Figure 14). Most of the Ste values were less than 3 m and concentrated below 2 m. This finding demonstrated that the Ste on the water-land boundary elevation was approximately 1 m in lakes with a water depth of 5 m or more. The deeper the lake water depth was, the lower the impact of the estimation error on the water surface elevation was. The average Ste of the water-land boundary elevation of lakes with water depth less than 5 m was ~0.2 m as shown in Figure 14(b). The figures revealed that lakes with shallow water depths exhibited a reduced fluctuation in the elevation of the water-land boundary. Consequently, this characteristic facilitated a more accurate estimation of the water surface elevation. However, a small number of abnormally large standard errors indicated fluctuations in the water-land boundary elevations of several lakes, which was contrary to the law that the lake water surface is approximately horizontal. The reason is explained in Section 5.

4.4.2. Analysis of water-land boundary accuracy

To further discuss whether higher spatial resolution remote sensing images and more accurate classification could contribute to better delineation of the water-land boundary, the study produced lake extent maps for a sample of lakes using higher spatial resolution images and estimated the elevations at the water-land boundary. The GSWED dataset was generated by applying a dynamic threshold to the Normalized Difference Water Index (NDWI), thus it was not an unique threshold in the entire study area, which makes it challenging to replicate it in our experiments. We applied a threshold of zero to NDWI to delineate the water surface. We used image data with two different spatial resolutions, i.e. one acquired at 30 m resolution by the Landsat Thematic Mapper and Operational Land Imager (OLI), and another was resampled to 90 m to match the spatial resolution of the DEM used. We compared these water extent estimates with the ones based on the 250 m spatial resolution data, which were the ones used to generate the JRC GSWD and GSWED datasets. The comparative analysis aimed to quantitatively examine the disparities in accuracy among results obtained from images of varying resolutions.

The same method described in Section 3.2 was used to delineate the water-land boundary and estimate the corresponding elevations. In addition to the two lakes mentioned in the previous section,

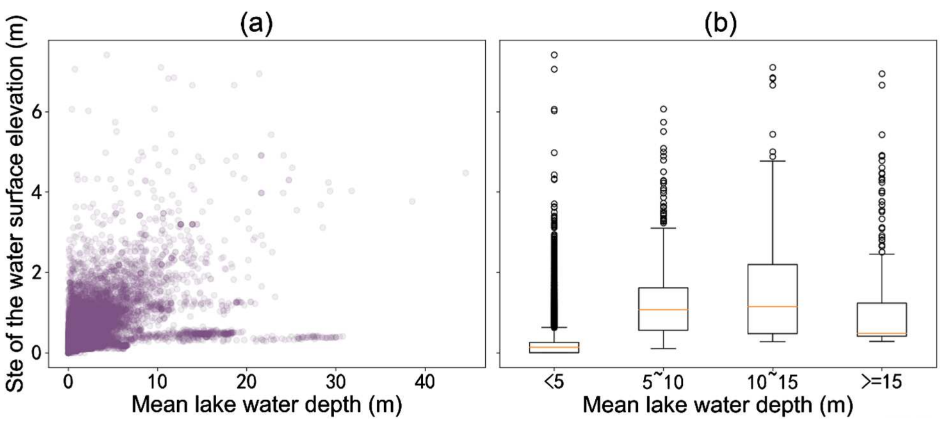

Figure 14. Ste of water-land boundary elevations: (a) all dry lakes and (b) different bins.

Table 3. Water-land boundary elevations of the lake extents at different spatial resolutions.

Lake (mean area)	Date	Spatial resolution (m)	Mean water surface elevation (m)	Ste (m)
Bui Reservoir (301 km^2)	2014/3	30	169.59	0.13
		90	169.73	0.16
		250	167.84	0.34
Samendeni Reservoir (103 km^2)	2020/1	30	319.48	0.07
		90	319.72	0.06
		250	320.12	0.10
Gilgel Gibe lake (36 km^2)	2018/11	30	1674.77	0.22
		90	1675.02	0.24
		250	1675.46	0.48

Lake Gilgel Gibe, located in a mountainous area, was chosen to evaluate the case of complex terrain (Supplementary Figure 4 and Table 3). The three lakes were located in different basins to evaluate the influence of different terrains. We explored 11 thresholds from −0.005 to 0.005 with an interval of 0.001 to extract the lake extent at 30 m spatial resolution. The mean water surface elevation and Ste were calculated by the same procedure to analyze the effect of threshold selection (Figure 15).

The water-land boundaries delineated with higher spatial resolution images were more accurate. Pixels at coarse spatial resolution were land-water mixtures, that led to the misclassification of water and land, thus to a less accurate boundary. When using the more accurate water-land boundaries to estimate the water surface elevations, significant improvements in the standard error statistics for Bui Reservoir and Gilgel Gibe lake were obtained, while there were few improvements in the standard error for Samendeni Reservoir. The mean water surface elevations estimated with image data at coarse spatial resolution were generally higher than the estimations based on higher spatial resolution images. In summary, the lake extents at higher spatial resolution significantly improved the accuracy of the water-land boundary and gave a smaller standard error. The water-land boundary delineated at higher spatial resolution was closer to the actual boundary and the errors on estimated elevation could be decreased by applying higher spatial resolution image data.

According to Figure 15, the mean water surface elevations decreased as the thresholds for distinguishing water and land got larger. The larger threshold usually led to extract a smaller lake extent. Due to the surrounding topographic trend of subsidence, the water surface elevations of water-land boundary got lower simultaneously. Following the law that the water surface of the lake is approximately horizontal, the elevations along the water-land boundary should be nearly equal. Therefore, the threshold was optimal when the Ste of the elevations of the water-land boundary reduced to the minimum as shown in Figure 15. The figures indicated that the optimal threshold for each lake was different, i.e. ∼−0.002 for Bui Reservoir, ∼−0.003 for Samendeni Reservoir, and ∼0.002 for Gilgel Gibe lake. The different spectral characteristics of lakes resulted in different optimal thresholds. Under- or over-selection of thresholds gave an offset in the water-land boundary, and the water-land boundary was not horizontal. This would increase the bias during estimating the water surface elevation, thereby impacting on the water depth. More accurate surface water maps would improve our estimates.

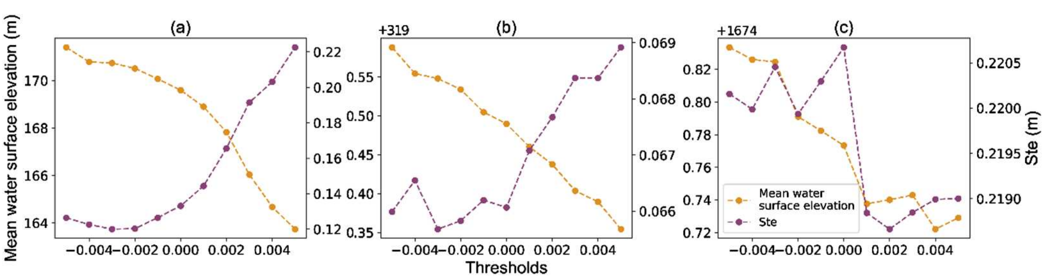

Figure 15. The mean surface water elevations and Ste of lake extents produced by different thresholds in (a) Bui Reservoir in March 2014, (b) Samendeni Reservoir in January 2020, and (c) Gilgel Gibe lake in November 2011.

5. Discussion

5.1. Lake water depth estimation methods

In the past few decades, significant improvements have been achieved in the estimation of lake water depth, but the latter remains the most problematic component of the lake essential properties due to the need to retrieve vertical underwater information from two-dimensional remote sensing data (Saylam, Brown, and Hupp 2017; Zhang et al. 2016). The method described in this study provides the estimation of the pixel-wise spatial distribution of water depth for the dry lakes whose lakebed were exposed. This pixel information enhances the understanding of the underwater characteristics better than the utilization of mean lake water depth. The proposed approach may exhibit relatively non-negligible errors in water depths. Nevertheless, its advantage, i.e. direct calculation of the difference between the water level and lakebed elevations of a lake, captures a realistic lake bathymetry. Moreover, bathymetry estimation by detecting lakebed topography is not limited to the existing DEM data, DEMs acquired in the future have the same potential to provide the elevations of lakebed for the lakes drying out at some point in time, thereby allowing for the retrospective estimation of historical lake water depths. The inclusion of spatial and temporal information on lake water depth promotes our comprehension of lake volume changes and key lake morphological characteristics (Cai et al. 2015; Verpoorter et al. 2014).

Despite achieving the estimation of water depth in the dry lakes, the method cannot estimate the water depth in lakes with unknown underwater topography. For those lakes, modeling of terrain elevation based on geo-statistics is the most widely used approach, whether it is by establishing the relationship between water surface elevation and lake area (Busker et al. 2019; Li et al. 2020) or predicting underwater topography from surrounding topographic characteristics (Delaney et al. 2022; Muñoz et al. 2020; Oliver et al. 2018). The challenge is to predict unknown underwater topography from surface information that can be derived from remote sensing images or altimeter data. In-situ measurements of lake bathymetry provide the most reliable solution and reference to retrieve underwater information from 2D images of the lake surface, but such measurements are not frequently available. This study also provides valuable data to complement in-situ data for training geostatistical models by means of remote sensing observations (Armon et al. 2020). Similarly, the proposed method is expected to provide lake bathymetry data on a global scale for water depth model training in the future, thereby enabling dynamic water depth estimation on all lakes.

5.2. Reference water depth data

Despite the fact that the lake training samples in HydroLAKES data on Africa are scarce, the available data are still valuable for validation of estimated water depth. This data set remains the only publicly available data on a global scale and is widely used. In our study, in Africa there are 99 lakes with HydroLAKES measurements and 68 measurements in 42 lakes by ICESat/ICESat-2 to add up to 167 measurements, i.e. a sufficiently large data set to evaluate our estimations in the 1235 lakes where the bathymetry was captured by SRTM DEM.

The global lake dataset HydroLAKES has been constructed by integrating several lake datasets, including Canadian hydrographic data, SRTM Water Body Data, MODIS water mask, and the European Catchments and Rivers Network System. As a consequence, lake data are based on observations, but are a mixture of lake measurements at different spatial resolutions and times. In the study area, the improved lake extent maps and HydroLAKES jointly include, 99 lakes with bottom topography exposed in February 2000. We consider that the HydroLAKES data set focuses on the 'extent' of lakes rather than 'changes' and might miss unstable lakes with bottom topography exposed in February 2000. Additionally, the temporal coverage of the two data is different, so that new appearing lakes were not recorded by HydroLAKES after 2016.

We consider that the reasons causing the difference between our estimates and HydroLAKES are multiple. First one is that the lack of information on the observation time of the HydroLAKES data makes it challenging to compare with our dynamic water depth point by point. Next, it is noticed that the training lakes in HydroLAKES are mainly located at America and Europe, but there are a few lakes in our study area (Messager et al. 2016), and they are located in the eastern part of the study area in the Great Rift Valley. Although the Messager et al. (2016) research proved that the estimates were accurate in the African lakes, lack of sufficient in situ measurements potentially increases the uncertainty of HydroLAKES in the study area. Finally, the reliance on training data primarily from large lakes in HydroLAKES to develop the depth estimation model could impact the accuracy of the estimates in smaller lakes. The unique characteristics and dynamics of small lakes might not be adequately captured by the model, resulting in the difference between the two datasets.

Furthermore, ICESat/ICESat-2 observations are independent observations considered as highly accurate (Feng et al. 2022; Hu et al. 2023), but there is still some error caused by the signal contamination and lake waves. The dates of acquisition of the data and the multispectral images were different, even though within the same month. This is one of the sources leading to the difference between our estimates and the ICESat/ICESat-2 observations. The ICESat/ICESat-2 footprints and the spatial resolution of the multispectral images are also different and the classification accuracy of the land surface water products have an additional impact on the estimated elevation of lake surface. The advantage of the proposed method is to provide estimates of lake water depth results at finer spatiotemporal resolution and similar accuracy as ICESat/ICESat-2, which is especially relevant to fill the gap between the two sensors.

5.3. Accuracy of water-land boundary

According to the finding in Section 4.4.1, a small number of abnormally large standard errors indicated fluctuations in the water-land boundary elevations of several lakes, which was contrary to the law that the lake water surface is approximately horizontal. We discuss the reasons causing the phenomenon, one of which may be the deviation in the position of the water-land boundary caused by the spatial resolution of the DEM. In addition, several other factors affect the delineation of the water-land boundary, such as accuracy of the land and water classification, particularly the impact of emerging vegetation and sub-pixel mixtures of water, vegetation and soil, and the choice of the line-type applied to delineate the boundary types. The maps of inland surface water bodies used in this study were obtained by applying a threshold segmentation method to NDWI or NDVI images (Han and Niu 2020; Pekel et al. 2016). The reliability and effectiveness of this method is documented in literature (Lv et al. 2019; McFeeters 2007; Xu 2007). There are multiple unsolved issues, i.e. wrong classification of objects that have non-unique spectral features with water and mixed pixels in the lake boundary, which makes accurate delineation a challenge (Wu et al. 2018; Yang et al. 2018). In some regions within our study area, e.g. in Ethiopia, volcanic rocks may be mis-classified as water because of similar spectral features with water. The mixed pixels that are inherent to the transition water to land result in scattered NDWI values within this transition zone. There is no satisfactory threshold that perfectly separates water from land. The uncertainty in the threshold to classify water and land can lead to an inwards or outwards deviation of the estimated lake boundary (Weekley and Li 2019), thus degrading its accuracy. The proposed method applies an equal width buffer zone on both sides of the estimated boundary, then the mean elevation within the buffer zone is estimated (Figure 4). Compared with the definition of boundary as the exterior or interior zone, the equal width buffer method is more accurate, since it will include samples with both higher or lower elevation than the correct one. Additionally, it should be noted that the method may be less accurate for lakes in a canyon. If the terrain near the water-land boundary is very steep and the DEM does not have high spatial and vertical resolutions, the large drop from the land elevations above and below the water surface may not be captured by the method described above, leading to large errors in the estimated elevation of the water surface. Datasets with better spatial-resolution and classification accuracy would be expected to reduce such undesirable effects in the future.

5.4. Vegetation interference

It should be noted that SRTM is a digital surface model and for many applications the surface features/artifacts caused by the vegetation canopy, present in SRTM, can cause significant errors. Contamination of the original terrain elevation by vegetation is one of the sources of uncertainty in the proposed method. The presence of vegetation has also a large impact on the accuracy of the water-land boundary. Previous researches demonstrated that the SRTM DEM is very accurate for uncovered terrain but does not capture the sub-canopy terrain due to the short wavelength of the SRTM SAR which cannot penetrate vegetation (Baugh et al. 2013; Li et al. 2022; Liu, Liu, and Alsdorf 2014; Rabus et al. 2003; Yang, Meng, and Zhang 2011). The vegetation signal retained in the DEM had a two-fold impact in this study. On the one hand, the overestimation of the lakebed elevation, when covered by vegetation, would lead to lower water depths. On the other hand, errors in the delineation of the water-land boundary would result in errors on water surface elevation, thus on water depth, which is also directly reflected in the large standard deviation in the elevations of the water-land boundary. Previous studies applied systematic or mathematical approaches to remove the vegetation signals which accounted for spatial variability using published global estimates of vegetation height and removed the portion of vegetation height from the SRTM DEM (Baugh et al. 2013; Liu, Liu, and Alsdorf 2014). Other authors applied the point-ground elevations by GLAS and ATLAS in combination with land use/cover maps to correct vegetation-related errors in the SRTM DEM (Li et al. 2022; O'Loughlin et al. 2016). Although the 'Bare-Earth' SRTM DEM used in the study partially remove the contamination of vegetation, residual errors past the application of such corrections remain to be evaluated.

5.5. Potential bottom topographical changes

The study assumed that the lakebed elevation would not change or change slightly over time, which is likely to be correct given the relatively short period covered by this study. In practice, the lakebed elevation may change under the influence of sedimentation, erosion, geologic disasters, and anthropogenic factors, which are important geomorphological processes (Chen et al. 2015; Sadeghian, de Boer, and Lindenschmidt 2017). The ecological process and the sediments carried by surface runoff accumulate on the lakebed and increase its elevation, with a spatial pattern determined by sediment transport and deposition. Mountain hazards, such as landslides and debris flows, usually occur over a short period of time and cause localized changes in the lakebed and surrounding topography (Wren and Davidson 2011). In addition, human activities are unpredictable factors in changing the lakebed topography. For example, people might excavate or fill the lakebed during the construction of dams or reservoirs. The standard error of the lake water surface elevations was $\sim$1.59 m for the Bui reservoir, against 0.78 m only for the Samendeni reservoir. A possible reason is that the lakebed elevation changed during the construction of the Bui reservoir.

6. Conclusion

This study proposes a low-cost but efficient method to integrate information on the temporal variability of the water-land boundary and lakebed elevation using remote sensing data. The key objective of this method is to obtain a complete map of the lakebed elevation. The proposed solution is to focus on lakes which were dry at the time of a DEM acquisition. In this study we used the SRTM DEM acquired in February 2000 and we focused on lakes which were dry at that time. The performance of the proposed method was demonstrated in the Sahel-Sudano-Guinean zone in Africa with variable climate and scarce in-situ observations. Generally, the proposed method can produce acceptable estimates of the lake water depth, which were highly consistent with the ICESat/ICESat-2 measurements and the HydroLAKES data. Furthermore, our estimation method can provide the detailed spatial distribution of lake water depth and complete time series as long as a lake contains water covered.

Although the proposed method provides accurate estimates of lake water depth in the lakes with known bathymetry, it cannot be applied to lakes with unknown bathymetry. We used in a companion study (manuscript in preparation) the estimated water depths in the dry lakes as reference data to build a relationship to estimate the lake water depth as a function of other lake basin characteristics, thereby predicting and estimating the water depth in the lakes with unknown underwater topography.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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