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Potential of multi-source Geospatial data in Accurately Estimating the Live Storage Capacity of Reservoir

Ghosh Natoo Nilima[1,2], Prasun Kumar Gupta[2], and Bhaskar Ramchandra Nikam[3]

[1] Geoinformatics Department, Indian Institute of Remote Sensing, ISRO, Dehradun, India
[2] Centre for Space Science and Technology Education in Asia and the Pacific, IIRS campus, ISRO, Dehradun, India
[3] Indian Space Research Organisation Headquarters, Bengaluru, India.

Corresponding author: Nilima Ghosh Natoo (nilima.iirs@gmail.com)

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Abstract

The two-fold pressure of ongoing rise in water demand and the impacts of prevailing warming climate are likely to exacerbate the shrinking of major water-bodies, especially in arid/semi-arid regions. Presently, assessment of live storage capacity (LSC) of any gauged reservoir needs water level observation and updated Area-Elevation-Capacity curve, whose concurrent availability is challenging for water managers. Recent studies highlight satellite altimetry as a game-changer for estimating water elevation and lake storage, especially useful for remote, inaccessible regions, where traditional gauging stations are scarce. Yet, these measurements carry inherent limitations due to data capture procedures. The motivation of the present study originates from exploring the benefits of using geospatial data, furthering efforts to reduce a number of limitations that causes uncertainties in estimating lake storage. This study aims to develop a novel geospatial-based methodology to remotely estimate the live storage capacity of reservoir and further limited by data availability. This methodology is based on trapezoidal rule using Area-Height relation, where incremental live storage capacity estimates of infinitesimally small layers between consecutive water levels (likely to vary between minimum drawdown level and maximum full reservoir level), culminates into a running cumulative reservoir storage capacity. The satellite imagery-based water-surface area and corresponding water elevation dataset were assessed for at least one water-year. Initial trials with field data were later replaced by altimetry data, and the latter was validated to make the methodology purely geospatial data based. The geospatial based LSC estimates of Ukai reservoir (Gujarat, India) gave an excellent match to the level of 5th decimal digit of accuracy (mean error 8.79e-06, standard deviation of error 9.11e-05, RMSE 9.10e-05 MCM, Bias 8.79e-06) when compared to that of observation-based estimates. The fusion of optical and SAR imageries reduced the revisit gaps and missing data points, especially during monsoon, thus allowing a temporally richer dataset of water surface area for the study period. In contrast, only single altimetry data source (27 days revisit) was available for Ukai reservoir. This coarse water elevation data was pre-processed using advanced cubic spline interpolation method to obtain regular, temporally-richer time series, and was validated. It is concluded that a novel methodology is developed that (a) can accurately estimate LSC of any gauged reservoir; (b) the estimated accuracy of LSC is mainly a function of availability of temporally-rich geospatial input (water surface area and validated water-level), and an apt computation platform allowing complex integral computation among other factors for accurate estimation.

1. Introduction

Ever-increasing water demands together with warming climate conditions are likely to continue shrinking of large lakes, especially located within the drying climatic zones (Luo et al., 2022). The lack of field hydrological water elevation observations is common and limits one to assess actual estimation of reservoir's storage dynamics and related assessments on disasters (like flood or drought). Several recent studies show that utilization of satellite remote sensing altimetry technology has been a boon to estimate water elevation and lake storage dynamics in remote locations. One of such studies (Luo et al., 2022) used laser altimetry data (ICESat/ICESat-2) to obtain water elevation and storage volume dynamics across global lakes more than 10 km^2 area for 2003-2020. They found that the measured changes in water storage dynamics varied with respect to climatic zones and basins. They also concluded that the larger lakes located in dry climatic zones might go through further shrinking if current conditions prevail.

At present, assessment of live storage capacity of any gauged reservoir is not possible without two input parameters: (i) original Area Elevation Capacity (AEC) curve, and (ii) current water level (WL) observation. Both these parameters can be obtained from respective departments. Water level data can also be extracted from altimeters. As a result, regression models can be constructed to estimate live capacities from different WL sources and compared if required. The satellite radar altimetry is considered highly valuable to obtain water surface heights of open ocean and inland water bodies with area greater than 100 km^2 (Du et al., 2021). It is however, noteworthy that there are several reasons highlighted (Du et al., 2021) and the references therein that make radar altimetry difficult to obtain detailed monitoring, such as (a) accuracy of smaller lakes (< 100 km^2) are limited by land contamination to the echo signals, (b) large space between two satellite ground tracks, (c) low along-track azimuth resolutions, (d) low temporal resolutions and (e) the inability of altimeters to obtain 2D water surface height observations. So, apart from other factors, wide spacing between altimetry tracks is to be checked upon for accuracy of elevation data. Uncertainty, sourced from sensor noise, atmospheric variability, human error, etc. - is an inherent part of remote sensing products. Its quantification is required to correctly develop, interpret and use satellite remote sensing derived measurements and models (Werter and Burggraaff, 2023). Primarily uncertainty is of two categories, systematic and random errors: (a) systematic errors affect the accuracy of a measurement and can lead to incorrect interpretations of data. Whereas, (b) random errors affect the precision of a measurement. Further details are given by Werter and Burggraaff (2023). Specifically, to the current study of hydrology, uncertainty may mainly relate to the temporal frequency of water level data availability, matching date of corresponding area, apart from reliability of the water elevation observation due to observing system's limitations. Embracing these limitations are essential to arrive at more accurate regression analysis model. A study (Liu et al., 2022) utilized GEE and ICESat-2 altimetry data to monitor changes in water level and volume of selected lakes and reservoirs in the Yellow river basin and concluded that (i) for lakes - uncertainty of water volume change estimation was mainly affected by the measurement uncertainty of water level change, however, (ii) for reservoirs - the combination of measurement of uncertainties of water level change and area both were reported to influence the estimated uncertainty of water volume change.

Some studies (Prandi, et al., 2021; Lin et al., 2023) highlighted the worth of including precise computation and application of uncertainties in determining the model performance as well as validating altimetry data. Comparison of radar altimetry measurements with that of independent field water level data as a process of validation must include uncertainties from various sources to prevent incorrect misinterpretations. Similarly, model evaluation against field water level data defines model deficiency and to avoid misinterpretation precise and validated uncertainties are necessary. The process would allow us to establish the best possible regression analysis model aiming at more accurate/reliable estimation of changing water volume. (Lin et al., 2020). The current study aims at using multiple sources, multiple sensors data such that the temporal gaps between consecutive data can be reduced, hence arriving at a lowest possible least count.

2. Materials and Methods

2.1. Study area

The Ukai reservoirs have been identified for analysis; each located at diverse hydroclimatic locations of India and are geographically distant from each other (**Figure 1**). First case is Ukai (Vallabh Sagar) reservoir, geographically located at western part of India (73.7073 °E, 21.3235 °N), constructed on Tapi river, Tapi district of Gujarat state of India, functional since 1972.

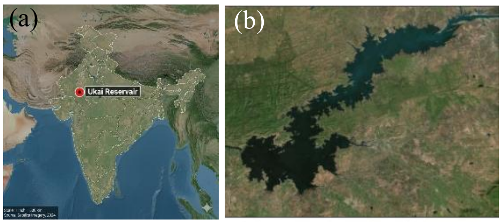

Figure 1 (a) Geographical location of Ukai reservoir (b) Base (satellite) map of the Ukai reservoir case-study, Gujarat (Tapi river)

2.2. Data

Estimation of storage capacity is an important factor in defining the functionality of any gauged reservoir. This study uses the advanced geospatial methodology to obtain changes in water storage capacity over a defined time-period. This requires remotely sensed dataset for both water body extent and water elevation of the same day. (a) Satellite Imageries (Google Earth Engine platform): Remote sensing satellite data from multiple sources (both optical and SAR imageries) were utilized to extract the water surface area (extent). Finer resolution optical data from Sentinel-2 and Landsat-8. The data from these passive sensors are useful only during non-monsoon months, where clouds do not hinder the satellite imageries. However, analysis during monsoon months covering full water-year, there are limitations due to presence of clouds over waterbody to be mapped. Therefore, many a times the data are irregular or completely missing during these months. To ensure accuracy in delineation of WSA over one complete water year, SAR satellite imageries have been found very useful due to their all-weather, day-night coverage. The contrast enriched with SAR data from Sentinel-1 were utilized to delineate the WSA accurately. **Table-1** gives an overview of three sources of satellite imageries, which were used to extract single resulting band, the "water-band", representing time-series of extracted WSA for Ukai (2021-2023). (b) Water Elevation (field gauge data and Altimetry) dataset: Two different sources of water elevation data have been collected, one from the remote sensing altimetry and second from the field gauge (observation) data. (i) The altimetry water level time-series for Ukai reservoir was downloaded manually from Database for Hydrological Time Series of Inland Waters (DAHITI, Schwatke et al., 2015). It is noteworthy that only Sentinel-3A (revisit time of 27 days) altimetry data was available for Ukai reservoir. The altimetry WL data is an essential source of data and forms the basis of remote computation of the storage capacity. In the absence of similar source of remotely sensed WL data, geospatial technology would not help in storage capacity computation, at least the new method that is being formulated in this study. (c) A baseline survey data of Ukai reservoir case study was collected from the Narmada Water Resources, Water Supply and Kalpasar Department (NWRWS, Kalpasar, Gandhinagar, Gujarat) in November 2024. The reference Elevation-Capacity data from Hydrographic Survey of Ukai in 2003 - formed the baseline data to compute the updated AEC curve, which is supportive in finding the changes in WSA contours. (d) Daily gauge data for selected time-period was available from India Water Resources Information System, WRIS portal. These field WL data were required to validate the altimetry-based coarse water elevation data for exactly the same study-period. Further, validation of storage capacity computed with altimetry data were validated with that computed using field observation data. The latter source of field WL data is essential to validate the storage capacity formulated in this study using only geospatial inputs (WSA, WL).

2.3. Methodology

A step-by-step schematic flowchart of all the major steps from pre-processing, decision-making, data analyses, validation, to visualization, along with brief on specific platforms where they were carried out to build-up the new method (or formulation) have been sketched out in **Figure 2.**

(a) Pre-processing temporally coarse WL time-series data: Temporal interpolation is basically a process of estimating missing records/data points in a given time-series, allowing real-world imperfect data collection creating continuous and complete dataset ready for analysis or comparison. Polynomial interpolation uses a higher degree polynomial to join discreet points to fit the curve. Whereas, the spline interpolation uses low degree polynomials in each interval such that the polynomial pieces fit smoothly together to form a spline. **(b) Addressing Altimetry Data Limitations via Interpolation:** Although RS technology is a boon to estimate water elevation and lake storage dynamics, lack of availability of temporally finer altimetry data limits its utility. Due to 27 days revisit time, Sentinel-3A (S3A) altimetry data for Ukai reservoir made the altimetry time series temporally very coarse (~monthly), meant that, only a 27-day coarser storage volume estimation could be achieved. This situation was further constrained by unavailability of multiple altimetry datasets for the study period. This limitation was resolved by adopting an advanced interpolation method to fill the gaps in WL records to obtain daily altimetry data. To closely mimic the real-world phenomena depicted by water elevation variation, the cubic spline interpolation technique was adopted where it fits a series of cubic polynomials between each pair of data points. Linear interpolation uses linear polynomial to fit a line between two points, alike equation of the line or simply joining two points by drawing a line between them.

Table-1 Table of multi-sensor satellite: Optical (Sentinel-2, Landsat-8) and SAR (Sentinel-1)

Satellite/Sensor	Details on Resolution			
Optical data	**Spatial**	**Spectral**	**Temporal**	**Radiometric**
Sentinel-2 (S-2, 13 bands) **10m, 20m**	Band 3, Green: 10 m Band 11, SWIR1: 20 m	Green: (560/559 nm) SWIR1: (1613/1610 nm)	S-2A = 10 days	12-bit Potential Light Intensity provides **2^{12} = 4096** Shades of Grey = (0-4095) from Black to White
Landsat-8 (L-8, 9 bands) **30m**	Band 3, Green: 30 m Band 5, SWIR1: 30 m	Green: (533-590 nm) SWIR1: (1566-1651 nm)	L-8 = 16 days	
SAR data				
Sentinel-1 (S-1) **10m**	C-band 10 m	3.75-7.5 cm 4-8 GHz	S-1A = 12 days	VV polarization (available) for study reservoirs

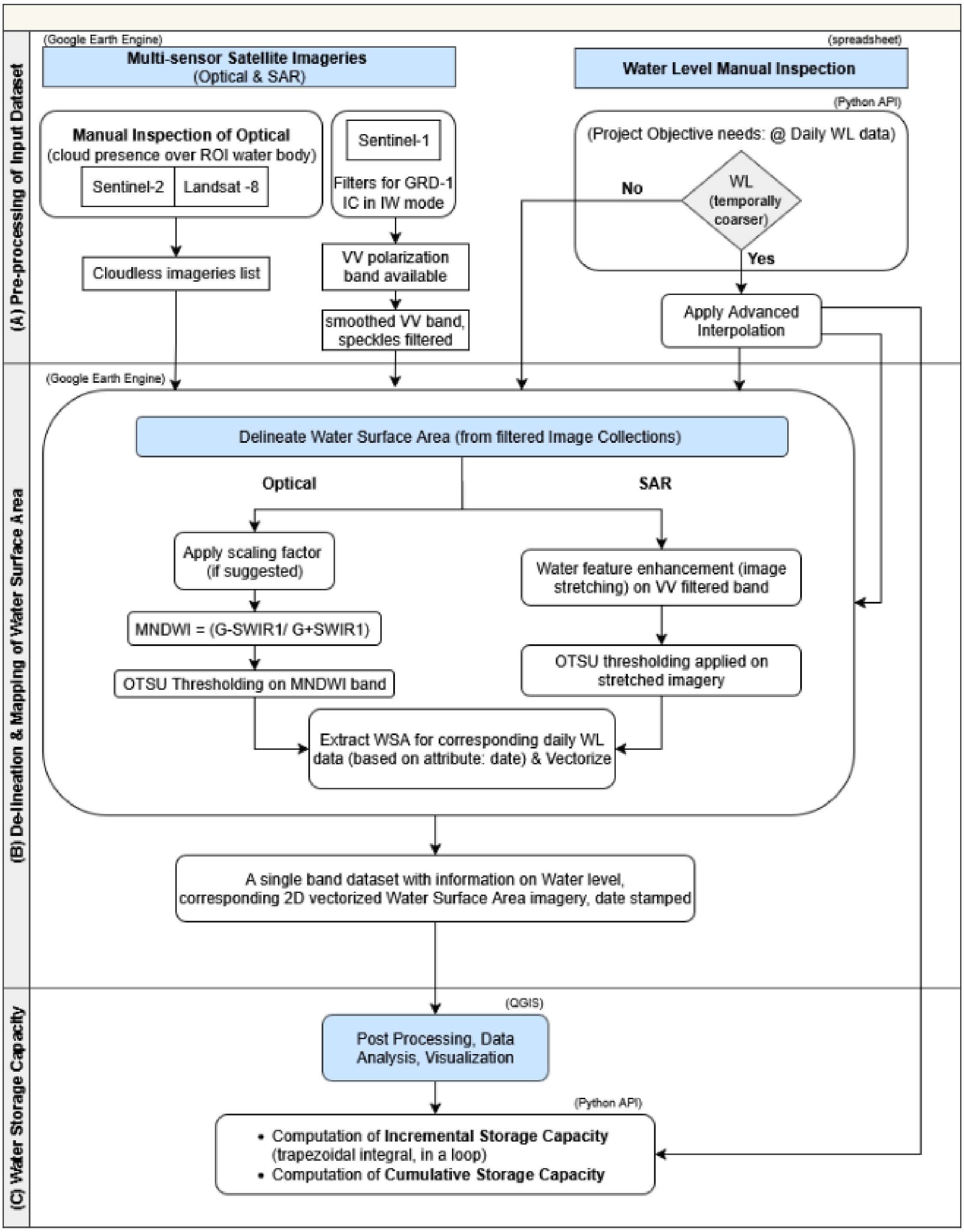

Figure 2 Flowchart showing different steps of input data processing, stages of analysis for water storage estimation including strategical elimination of identified uncertainties

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Polynomial interpolation uses a higher degree polynomial to join discreet points to fit the curve. Whereas, the spline interpolation uses low degree polynomials in each interval such that the polynomial pieces fit smoothly together to form a spline. In python notebook, this can be implemented using the Scipy. This intermediate pre-processing of altimetry data was necessary to ensure finer resolution storage capacity time-series. The strategy in gap filling the missing data greatly helped in reducing the uncertainty in altimetry-based storage capacity calculation.

(c) Delineation of Water Surface Area (WSA): Careful manual inspection of individual optical satellite imageries was done to eliminate imageries with presence of cloud over the selected ROI (waterbody); thereby allowing imageries with clouds present over non-water pixels in the final screened list of cloud-free optical (Sentinel-2 and Landsat-8) imageries). The extraction of WSA uses thresholding on selected spectral index, such that the sensitivity of land-water spectral behaviors is used to delineate the waterbody. The Modified NDWI index suggested (Xu et al., 2006) based upon the sensitivity of water to green (reflects) and SWIR (absorbs even lower than Near Infrared) bands, which is more sensitive than NDWI in distinguishing and eliminating noise from built-up pixels, like bridges (Du et al., 2016 and Sun et al., 2012). Several studies (Kolli et al., 2022 and Du et al., 2016) demonstrated its usefulness. An automatic Otsu thresholding method, which can compute the optimum threshold value based on the maximization of the between-class variance in the foreground and background pixels in the image (Kolli et al., 2022) was adopted to separate water pixels from background image. More information on image segmentation using OTSU thresholding is given in several literature (Nobuyuki Otsu, 1979; Bangare et al., 2015; Srinivas et al, 2019) among others.

(e) Reservoir storage capacity estimation: Before understanding how to compute the water storage capacity, some basics related to reservoir and geospatial method is explained using **Figures 3 (a to c)**. The general relationship of Area-Height method (Water Storage, 2019) is illustrated using **Figure 3c**.

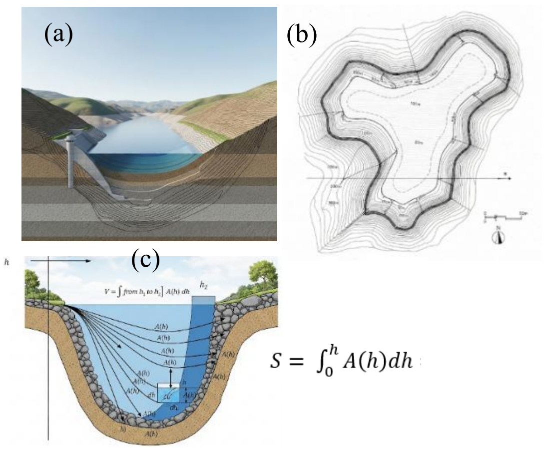

Figure 3 (a) Cross-section of a reservoir, (b) Changing contours of reservoir over a period of time, (c) Trapezoidal rule for live storage capacity (LSC) using Area-Height method (depicted by the integral relationship)

This mathematically can be represented by equation (1) and forms the basis of estimation of the incremental live storage capacity of a trapezoidal slice formed between two instances, say t_1 and t_2

$$S = \int_0^h A(h)dh = \int_0^A h(A)dA \tag{1}$$

More specifically, to compute the volume of water in a reservoir, a tank, or a river segment, one may use an approach where infinitesimally small volumes of water at each height may be added up to obtain running cumulative volume. In other words, the cumulative volume is computed by integrating the cross-sectional area (A) as it changes with height (h).

$$S_{1,2} = \int_{h1}^{h2} A(h)\, dh \tag{2}$$

Here, $S_{1,2}$ is the total volume, *A(h)* is the cross-sectional area at any given height h, and the integration is performed from a starting height *(h_1)* at time t_1, to adjacent height (*h_2)* at time t_2. The vertical axis representing the height, denoted by h; a series of horizontal cross-sections at different heights, *(A_1, A_2, A_3,..)* depicting the logic of a reservoir is likely to be wider at the top and narrower at the bottom. **Figures 3c** visually demonstrates the running cumulative volume computed over all the infinitesimally small layers of water levels varying between minimum (~MDDL) and maximum (~FRL) water levels.

Following above concept, two different approaches were adopted to compute the incremental volume between two consecutive instances (say, time t_1 and t_2), each with respective values of water-levels and cross-sectional water-surface (extent/boundary) area: Average-End-Area (simpler) method and Prismoidal formula (little complex method), each ruled by trapezoidal principle. Although both are used to compute volume of a segment between two consecutive (or) parallel cross-sections, they differ in basic assumptions on the shape of the solid, therefore also differ in accuracy and complexity. *Average-End-Area method:* This is a simpler method, assuming the volume between two consecutive cross-sections is a trapezoidal prism. It calculates the volume by averaging the two end areas and multiplying by the distance between them, mathematically represented by equation (3).

$$S_{i,i-1} = \frac{\Delta h}{2}[A_i + A_{i-1}] \tag{3}$$

At times when the end areas differ significantly or when the shape between them is irregular, the computed volume may be less accurate and may tend to overestimate the true volume. *Prismoidal method:* This formula is based on one of the variations of the prismoidal rule (derived from Simpson's rule) and assumes the volume is a prismoid, a solid with two parallel end faces and trapezoidal sides, mathematically given by quation (4).

$$S_{i,i-1} = \frac{(h_i - h_{i+1})}{3} * (A_i + A_{i-1} + \sqrt{A_i * A_{i-1}}) \tag{4}$$

The term $\sqrt{A_i * A_{i-1}}$ is a geometric mean that corrects for the error in the simpler end-area method. As it accounts for the gradual change in area between the two ends, the prismoidal method is likely to provide more accurate estimates. For large scale projects, like reservoirs the method of volume calculation with a prismoidal correction included (always subtractive to the average-end-area method), though more complex, yet found more accurate. This trapezoidal integration when implemented in python platform facilitated error free computation of incremental volumes with smoother culmination into cumulative reservoir volume estimate, whose profile closely matched with that of both the water level profiles.

(f) Python platform and libraries used for data processing: Python platform was utilized for both pre- and post-processing. Pandas library was utilized for reading and analyzing the Comma Separated Values (CSV) files. Pandas were helpful in computing incremental volume between two consecutive water levels and their corresponding contour areas. SciPy, Matplotlib and Standard Python libraries were utilized in this work.

2.4. Results & Discussion

Estimation of live storage capacity: A novel methodology has been formulated to compute the incremental capacity between two instances to obtain total volume. Different steps of computation along with strategies incorporated to resolve identified sources of uncertainty that might add to the cumulative error in the resulting total have been detailed out (refer Figure 2 flowchart). **(a) Water elevation** data, sources of error and solution: Availability of multi-sensor altimetry data helps resolve temporal coarseness; however, it was not available for current study case Ukai reservoir. The cubic spline interpolation method was used and found to fit very well resulting in smooth, accurate curve from monthly data point interval to daily WL data (**Figure 4**).

Availability of coinciding (same date) field WL data at same datum (ground truthing data). Daily observation (gauge) data were available from WRIS portal. It was further utilized for validating the resulting storage capacity accuracy. **(b) Water surface area** (WSA) delineation, data, errors and solution: Manually cloud filtered set of optical satellite imageries were considered for the current methodology. Presence of clouds over waterbody were eliminated from the set whereas clouds present over elsewhere on the imagery was accepted. Utilization of multiple-sensor satellite imageries allowed temporally finer WSA dataset processed on GEE platform for each reservoir, ensuring more accuracy in obtaining near-regular input for storage capacity. With daily water-elevation data available, the algorithm looks for corresponding date's WSA available from the dataset. **Table 1** is followed where a brief on optical and SAR satellite image properties is given. MNDWI based automatic global OTSU thresholding for different sensors (S2, L8, S1) data helped accurate unbiased land-water delineation. The optimal thresholding was automatically chosen within the variance of the imageries in question. GEE platform allowed the computational power to analyse enormous data within minutes.

Figure 5 illustrates the dynamics of temporally varying WSA extent over one water year. **(c) Incremental storage capacity estimation, errors and solution:** Computation of incremental capacity is based on trapezoidal integral rule. The algorithm formulated in the python notebook allowed the incremental volume loop to correctly compute live instantaneous live volume within two immediate instances correctly.

Table 2 Ukai Statistical indices are tabulated for two methods applied for computing volume from satellite data inputs

	Method-1	**Method-2**
Mean Error	8.79e-06	2.54e-05
Standard Deviation of Error	9.11e-05	0.0001
RMSE (MCM)	9.10e-05	0.0001
Bias	8.79e-06	2.54e-05

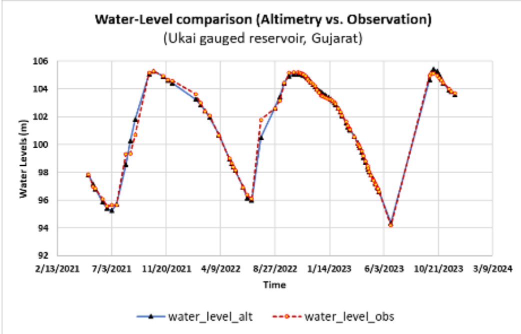

Figure 4 Comparative water-elevation charts (altimetry vs. field gauge) showing water level variation for (a) Ukai [2019-2020]

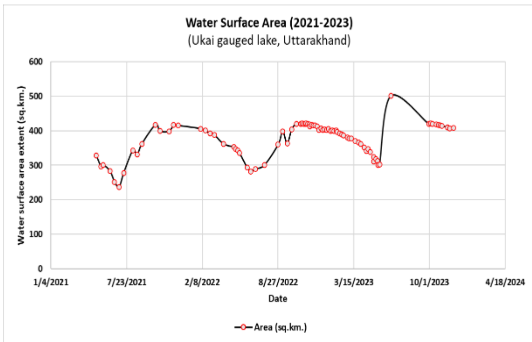

Figure 5 Variation in Water Surface Area extent (a) Ukai (2021-2023)

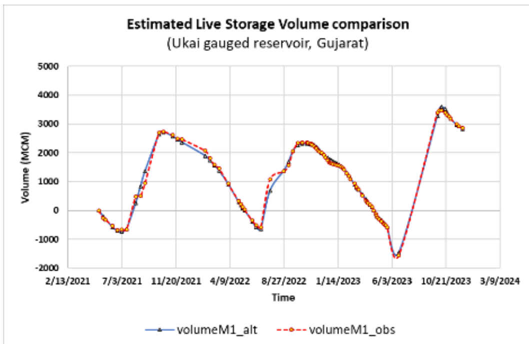

Figure 6 Comparative chart presenting estimated live storage capacity (volume) using altimetry and field observation water levels for (a) Ukai reservoir

Hence the cumulative error propagation in total storage capacity for one water year was nullified. **(d) Advanced platforms:** Right from pre-processing, ingestion of input data and computation of WSA, interpolation or estimation of incremental and total storage capacity, the advanced tools, methods and platforms like GEE, python API and the tools allowed handling of massive image collection, processing and accurate computation loop, reducing most identified errors and uncertainties during the study and learning. The resulting estimated storage capacity for Ukai reservoir are plotted for selected study period (**Figure 6**).

Validation of estimated storage capacity: The estimated storage capacity with altimetry data were validated with reference to the observation-based capacity computation and statistical error indices were used to select the best among the two as shown by the **Table 2**. Further error and percent error variations between the two set of estimated live storage volume were also plotted (**Figure 7**).

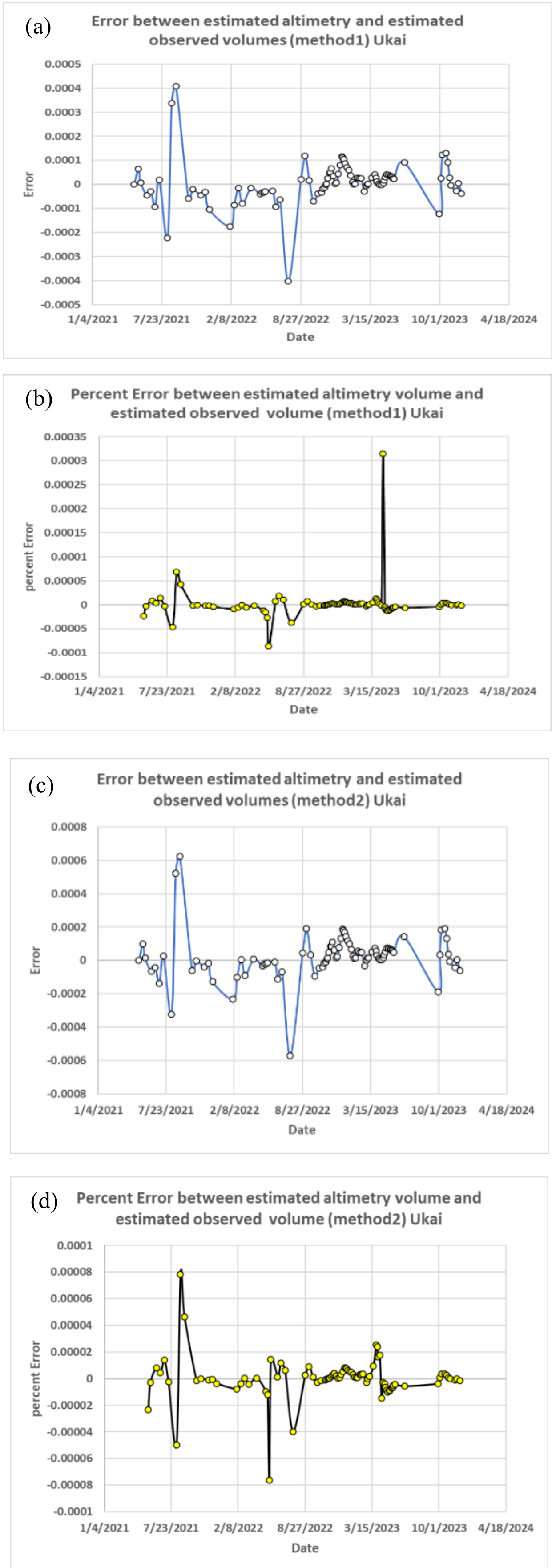

Figure 7 Ukai reservoir - Error and Percent Error variation between estimated altimetry volume with that of estimated observed volume. Plots (a) and (b) depicts error and percent error for method-1; plots (c) & (d) depicts error and percent error for method-2

Plots (a) and (b) depicts error and percent error for method-1; plots (c) and (d) depicts error and percent error for method-2. In case of Ukai reservoir, method-1 outperforms method-2.

Discussion: The study presented a novel methodology that can accurately estimate LSC of any gauged reservoir purely based on geospatial technology and data, completely eliminating the need of field gauge dataset. This was illustrated compressively by Ukai reservoir where comparison of capacity was made between traditional (observation based) and purely altimetry-based estimation, where latter was found accurate up to 5th decimal degree. This aligns with findings in similar studies (Zhang et al., 2020), who reported that advanced algorithms and data processing techniques significantly enhanced the accuracy of reservoir storage estimations by reducing systematic errors. The successful application of cubic spline interpolation for smoothing the water level data also reflects the importance of advanced data processing techniques, as highlighted in previous literature (Alfieri et al., 2021), who emphasized the necessity of high-resolution data for accurate hydrological modeling.

A reasonably accurate method for estimating the live storage volume of gauged lakes is developed, given geospatial input data: temporally rich cloud-free satellite imageries and rich water level (observation or altimetry) data. The reduction in uncertainity were taken care via a number of factors, like screening manually the cloud-free (over region of interest, especially the selected water body); input data pre-processing - like including multiple sensors' imageries for extracting water boundary extent, to detect outliers, interpolation of coarser altimetry data using advanced interpolation (cubic spline) method to grab and utilize area from each imagery available for the region of interest. The fusion of optical and SAR imageries further shortens the revisit times ensuring reduced uncertainty due to increased imageries available for the same study period. Similar concept stands true for the altimetry data when considered from more than single source, however, multiple sensor data were not available for Ukai study case for the study period. Based on the experiments forced by altimetry (monthly) data and interpolated daily data, it is concluded that finer temporal resolution water level data is necessary to utilize all available satellite imageries for the study area. In absence of fine temporal resolution water level data, one may adhere to an advanced method of temporal interpolation. For those reservoirs with observation data available (even if coarser), one must validate the interpolated altimetry to observed data to check near-match between the two time-series. This will ensure a correct estimate and profile of volume. Further to the availability of finer TS WL, corresponding area of same date is necessary for precision. In case of gauged reservoirs, an additional step of validation of altimeter water level with that of observation WL ensures the quantification of uncertainity in volume computation.

From these results and discussion, it can be concluded that the uncertainity in volume estimation is mainly a function of the temporal frequency of WL data availability, matching date of corresponding WSA, appropriate platform to precisely compute incremental volume formulation in a loop. These conclusions are supported by several authors (Du et al., 2021; Prandi, et al., 2021; Liu et al., 2022; Werther and Burggraaff, 2023). Hence it is concluded that the geospatial altimetry data can successfully replace the gauge data from field observation for any gauged lake.

2.5. Conclusion & Outlook

Unlike traditional methods that may rely on less precise gauge data or simpler computation techniques, this study utilizes advanced platforms and algorithms (like Python, GEE) to handle large datasets and perform accurate computations. The study's focus on pre-processing input time-series datasets, including the use of cubic spline interpolation for filling gaps in altimetry data, showcases a more sophisticated approach compared to many existing studies that may not address temporal coarseness effectively. Moreover, the validation of estimated storage capacities against observation-based computations and the detailed statistical analysis of errors further ensures the reliability of the results.

Looking into the criticality of rising glacial lakes through the lenses of changing climate, this established (gauged lakes) method can be refined to compute storage capacity of the natural (ungauged) glacial lakes, project its likely future dynamics and map susceptibility risk scenarios for downstream communities due to potential **G**lacial **L**ake **O**utburst **F**lood and cascading water related disasters. Secondly, similar studies on a wider variety of reservoirs with different geographical and hydrological characteristics could validate the generalization of this methodology. Integrating machine learning techniques to analyze and predict water elevation and storage capacity could help in implementing long-term monitoring programs.

2.6. Acknowledgement

The authors are grateful to Water Resources Authority of Ukai Reservoir (Narmada, Water Resources, Water Supply and Kalpasar Department, Gandhinagar, Gujarat) for providing the elevation-capacity data. The authors acknowledge WRIS for water elevation gauge records; GREALM and DAHITI portals for altimetry data sources. The first author extends special gratitude to various online/offline, technical, programming tutorials, especially those from Spatial Thoughts that not just made learning convenient, code organized but also motivated her to search and opt for newer, advanced methods to resolve sources of uncertainties in intermediate results before moving to the next step. The authors are grateful to the reviewers for their genuine feedback and efforts in bringing the article into more expressive piece of research work.

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