Global Assessment of Reservoir Water Storage Capacity and Sedimentation Rates Using Remote Sensing and Machine Learning

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1. Abstract

Reservoirs play an important role in water resource management, yet global monitoring of their storage dynamics remains challenging due to sparse in-situ data. This study addresses this gap by integrating remote sensing (Sentinel-2 MSI), geospatial databases (HydroLAKES, Global Dam Watch), and machine learning (LSTM, XGBoost) to estimate reservoir storage and sedimentation rates at scale. We developed an automated Python-Google Earth Engine (GEE) pipeline that extracts monthly spectral indices (e.g., NDWI) and Sentinel-2 band metrics (2018–2023) for 25,334 reservoirs, merging them with static hydromorphometric attributes (e.g., capacity, elevation).

To validate our approach, we aligned NDWI-derived storage estimates for Fuqua Reservoir (USA) with USGS gauge data, achieving RMSE = 19.7 Mm^3, MAE = 16.1 Mm^3, and MAPE = 62.9%. For forecasting, we compared LSTM and XGBoost models against an NDWI-capacity baseline, finding that NDWI alone explains >60% of storage variance, while additional spectral bands (e.g., B8, B11) and static features (e.g., catchment area) reduce error metrics. Our framework demonstrates that satellite-derived indices can approximate reservoir volumes where ground measurements are absent, though limitations persist in low-water conditions.

Key contributions include:

- A scalable pipeline for global reservoir monitoring using open-source satellite data.
- Interdisciplinary validation linking remote sensing with hydrology and civil engineering.
- Machine learning insights on feature importance for storage prediction.

Future work will integrate high-resolution bathymetry and hydrometeorological data to refine sedimentation estimates. This study advances sustainable water management by enabling near-real-time reservoir assessment without reliance on physical gauges.

2. Introduction

This project lies at the intersection of data science (Data) and environmental engineering/hydrology (X). We use remote sensing, geospatial analytics, and machine learning to address a critical gap in global water resource management

2.1 Problem Definition & Significance:

Reservoirs are essential for agriculture, hydropower, and drinking water. They face increasing threats from sedimentation and climate variability, and most lack consistent monitoring due to cost and logistical barriers. The first issue that my project deals with is the fact that most countries that share the same basin face issues with sharing data with one another, hence there are a lot of reservoirs that lack robust hydrological data. We can use satellite data with hydrologic modeling to solve this gap.

Another issue is with the fact that over 50,000 large dams worldwide store ~7,000 km^3 of water, but sedimentation reduces their capacity by 0.5–1% annually, jeopardizing water security and infrastructure longevity (Lehner et al., 2024). Remote sensing can be used to quantify the amount of water lost to sedimentation buildup by calculating the water difference relative to total reservoir storage capacity.

Traditional reservoir monitoring method rely on sparse in-situ gauges, leaving a huge majority of reservoirs unmarked, and lacking data. In fact, our unified dataset from taken both Hydrolakes and GDW had around 1.4 million+ reservoirs but only around 35,000+ of these resevoirs have official names and even a smaller percentage of these 35k reservoirs have groundtruth and day-to-day gauge data. This gap impedes climate adaptation and transboundary water-sharing agreements. We tackled this problem by:

- Automating storage estimation using freely available Sentinel-2 time series data.
- Quantifying sedimentation trends via time-series machine learning.

2.2 Research Questions & Hypotheses:

- RQ1: Can Sentinel-2 spectral indices (NDWI) and static reservoir attributes reliably estimate water storage capacity?
    - Hypothesis: NDWI correlates strongly with storage ($R^2 > 0.6$), with improvements from auxiliary bands (B8, B11) and morphometrics (e.g., capacity, elevation).
- RQ2: How do machine learning models (LSTM vs. XGBoost) compare to empirical area-volume curves in predicting storage?
    - Hypothesis: LSTMs outperform linear models by capturing temporal dynamics (MAPE < 50%).

2.3 Broader Impact and Significance:

A lot of my work contributes to UN Sustainable Development Goal 6 (Clean Water) becuase of the reservoir management aspect. I like how my project demonstrates how data science can help in environmental monitoring, particularly in low-resource regions, such as unnamed reservoirs found in GDW and HL dataset. Some practical motivations would include the fact that water managers need the means to measure water storage but are impeded to do so due to the limitation imposed by transboundary water-sharing agreements. Remote sensing can be employed to make information about such transboundary basin available to both sides of the party. On the field of remote sensing, my project advances this field's research through the results of my models, what machine learning models are best. The pipeline that i've built and plan to open-source, of which researchers can replicate to estimate water storage, and lastly what bands to use, as previous works rely on a smaller range of bands.

3. Related Work

3.1 Previous Research in Remote Sensing for Reservoir Monitoring
Prior work has established the viability of satellite-based reservoir monitoring, though with key limitations. Early efforts like the Surface Water and Ocean Topography (SWOT) mission and Global Reservoir and Lake Monitor (G-REALM) demonstrated the potential of altimetry and optical fusion for large reservoirs (Birkett et al., 2010; Gao et al., 2012). However, these systems focused on major dams, omitting smaller reservoirs critical for regional water security (Messager et al., 2016). We also see that recent advances in Sentinel-2 MSI imagery enabled higher-resolution surface-area mapping (Donchyts et al., 2022), while studies like Yao et al. (2023) combined Sentinel-2 with USGS gauge data to infer sedimentation rates—albeit only for well-instrumented sites.

3.2 Data-Driven Approaches in Hydrology (X Domain)
In hydrology, area-volume curves (Pimenta et al., 2025) and hypsometric integration (Yao et al., 2023) have been used to convert surface-area estimates to storage volumes. The HydroLAKES and Global Dam Watch (GDW) databases (Lehner et al., 2024) provided foundational geospatial inventories, but they lacked dynamic storage data. Machine learning applications, such as LSTMs for reservoir inflow forecasting (Pham et al., 2018), were limited to local scales due to sparse training data. We mostly worked with the GDW and HydroLAKES database to build our dataset, and compare our methods/improve on the work of Yao et al. (2023), Pham et al. (2018), and Pimenta et al. (2025).

3.3 Gaps Addressed by This Project
Scalability: Prior studies relied on manual workflows (e.g., per-reservoir JavaScript payloads in GEE) or region-specific models (Yao et al., 2023). Our automated Python-GEE pipeline processes 25,334 reservoirs globally, integrating static (HydroLAKES/GDW) and dynamic (Sentinel-2) data. We also contribute to the feature Innovation aspect in remote sensing: as NDWI is well-established for water surface area delineation (McFeeters, 1996), our work shows that other Sentinel-2 bands (B8, B11) and static morphometrics (e.g., elevation) improve storage predictions—this was previously overlooked in area-volume curve approaches. We also make a smaller contribution to limitations with ground-truth: most papers in this space rely on costly bathymetric surveys such as sedimentation studies like the RESSED database). Our method minimizes reliance on in-situ data by using NDWI-derived proxies validated against USGS gauges (RMSE = 19.7 Mm^3), which is freely available.

4. Data and Methodology

4.1 Crafting a unified dataset from GDW and HydroLAKES

Our study integrates two global geospatial inventories to create a comprehensive reservoir monitoring framework:

Global Dam Watch (GDW):

- Records: 35,295 dams
- Attributes: Design capacity (CAP_MCM), dam dimensions (height/length), construction year, ownership, and quality flags.

HydroLAKES (HL):

- Records: 1,427,688 lakes/reservoirs (≥10 ha)
- Attributes: Precise geometries, surface area, mean depth, volume, elevation, and catchment area.

Unified Dataset (GDW + HydroLAKES):

- Total merged records: 35,646
- Columns: 90
- Matched reservoirs: 25,334 (71.1%)

In-depth database querying results:

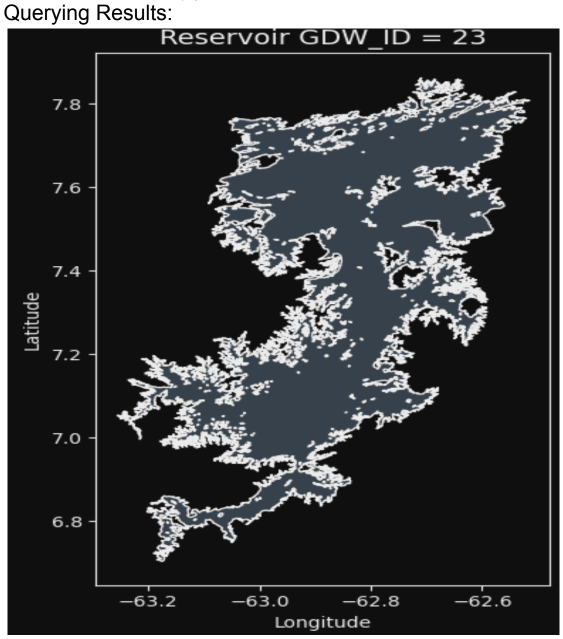
Loading GDW reservoirs...
GDW records: 35295
Loading HydroLAKES polygons...
HydroLAKES records: 1427688
Computing GDW centroids...
Performing spatial join…

Unified CSV (Hydrolakes and GDW):
Loading unified CSV…
Rows: 35,646
Columns: 90

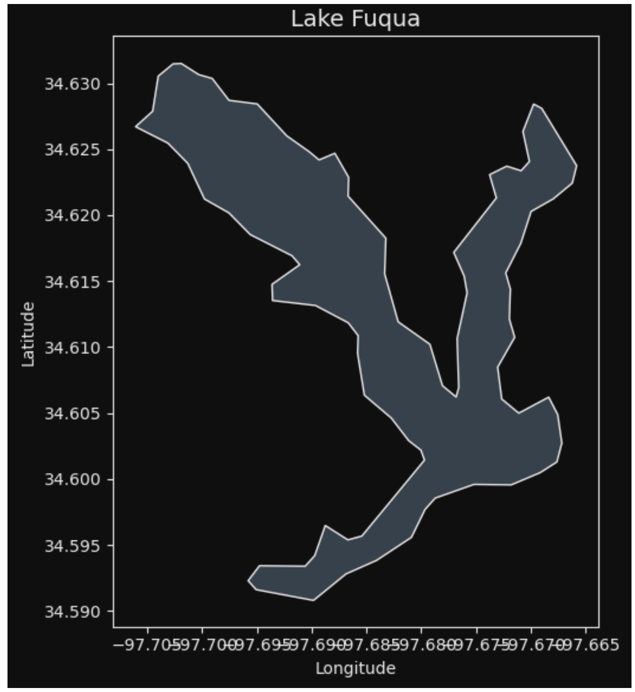
Column names:

```
column_defs = {
   "GDW_ID":      "Unique identifier in the Global Dam Watch database",
   "RES_NAME":    "Name of the impounded waterbody (reservoir or lake)",
   "DAM_NAME":    "Name of the dam or barrier structure",
   "ALT_NAME":    "Alternate or historic name, if any",
   "DAM_TYPE":    "Type of barrier (Dam, Lock, Lake Control Dam,)
   "LAKE_CTRL":   "Flag if this structure controls a natural lake",
   "RIVER":       "Name of the river on which the dam is built",
   "ALT_RIVER":   "Alternate river name or spelling",
   "MAIN_BASIN":  "Name of the major hydrologic basin",
   "SUB_BASIN":   "Name of the sub-basin",
   "COUNTRY":     "Country where the reservoir lies",
   "SEC_CNTRY":   "Secondary country if transboundary",
   "ADMIN_UNIT":  "First-order administrative region (state/province)",
   "SEC_ADMIN":   "Secondary administrative unit, if any",
   "NEAR_CITY":   "Nearest city or town",
   "ALT_CITY":    "Alternate or historic city name",
   "YEAR_DAM":    "Year the dam was completed",
   "PRE_YEAR":    "'Built before' year when exact date unknown",
   "YEAR_SRC":    "Source of the year information",
   "ALT_YEAR":    "Alternate construction year (e.g. modification)",
   "REM_YEAR":    "Year of removal or destruction, if applicable",
   "TIMELINE":    "Status change flag (Planned, Modified, Removed,
```

Unique Hylak_id: 25,325
Matched → HL polygons: 25,334 / 35,646 (71.1%)
Querying Results:



etc.)",
"YEAR_TXT": "Human-readable summary of construction year",
"DAM_HGT_M": "Dam height in meters",
"ALT_HGT_M": "Alternate dam height for secondary structures",
"DAM_LEN_M": "Dam length in meters",
"ALT_LEN_M": "Alternate dam length for secondary structures",
"AREA_SKM": "Reservoir surface area in km² (most reliable)",
"AREA_POLY": "Surface area computed from polygon geometry (km²)",
"AREA_REP": "Reported surface area from external sources (km²)",
"CAP_MCM": "Storage capacity in million m³ (most reliable)",
"CAP_REP": "Reported storage capacity (million m³)",
"DEPTH_M": "Mean depth in meters",
"DIS_AVG_LS": "Long-term avg. discharge at dam site (L/s)",
"DOR_PC": "Degree of regulation (% of annual flow stored)",
"ELEV_MASL": "Reservoir elevation above sea level (m)",
"CATCH_SKM": "Upstream catchment area (km²)",
"POWER_MW": "Hydropower capacity (MW), if any",
"MAIN_USE": "Principal reservoir use (Recreation, Irrigation, etc.)",
"QUALITY": "Data quality index (1=Verified .. 5=Unreliable)",
"EDITOR": "Initials of the data curator/institution",
"ORIG_SRC": "Source dataset for the dam point",
"POLY_SRC": "Source dataset for the shoreline polygon",
"HYLAK_ID": "Matching HydroLAKES polygon ID",



Justification, Reproducible Details, and Explanation of GDW and Hydrolakes Merging:

To build a comprehensive per-reservoir database, I joined the Global Dam Watch (GDW) and HydroLAKES (HL) inventories via spatial intersection on pour-point centroids. HydroLAKES contributes precise reservoir geometries and morphometric metrics—surface area, mean depth, total volume, drainage area, elevation, and residence time—for 1.4 million lakes, while GDW supplies dam-specific attributes—design capacity (Cap_mcm), dam height/length, construction year, ownership, and quality flags—for 35 295 barriers. After co-registering 25 334 GDW entries to their matching HL polygons (~71 % coverage), we produced a unified CSV of 35 646 records × 90 columns that merges both static and hydrologic metadata. This enriched table underpins our GEE queries (to extract 13-band monthly statistics) and feeds directly into downstream LSTM and XGBoost models. The reproducible detail is that users can also replicate this using a simple python script that follows the filepath:

Hydrolakes filepath:

- Python Project/Datasets/HydroLAKES_polys_v10.gdb

GDW filepath:

- Python Project/Datasets/25988293/GDW_v1_0_gdb
- Python Project/Datasets/25988293/GDW_v1_0_shp

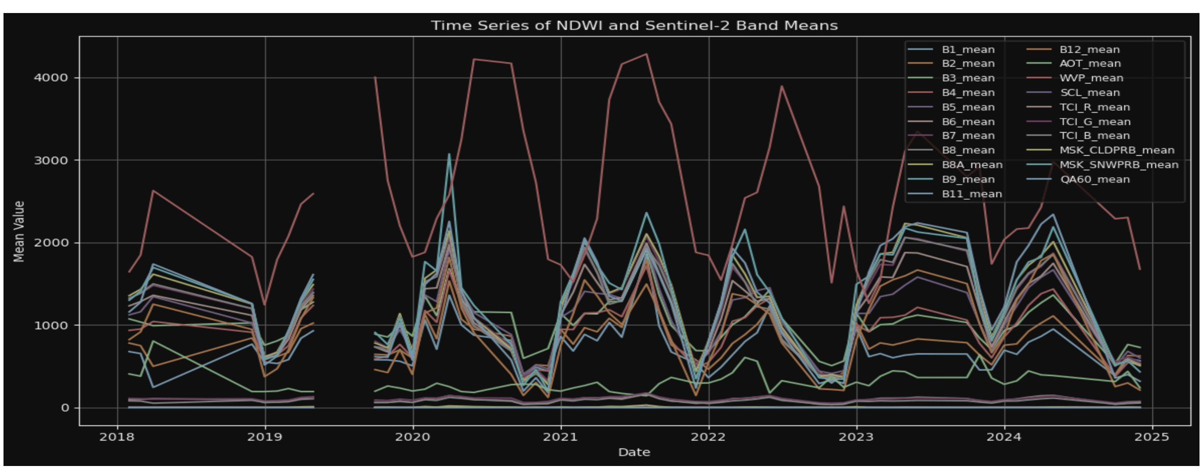
To justify the use of both datasets, we selected both GDW and HydroLAKES because of their high cross-coverage—GDW provides critical dam attributes (e.g., design capacity) while HydroLAKES offers globally consistent geometries, enabling scalable analysis of reservoir dynamics. The cross-matching reservoirs was high at 71%. I tried on other datasets, but most other datasets covered vastly different reservoirs, and the matching rate was <50%.

4.2 GEE segment

The GEE segment builds on the previous section. Now that we have the polygonal coordinates and static morphometric data for each polygon, we package them into javascript payloads and upload them into the Google Earth Engine. I automated an end-to-end extraction of monthly multispectral statistics (including NDWI) for each reservoir using the Google Earth Engine (GEE) Python API and geemap. The pipeline process documentation is as follows:

1. **Authenticates & initializes** EE via a service-account JSON and the ee Python client.
2. **Loads** each reservoir polygon (GeoJSON → EE Asset → ee.FeatureCollection).
3. **Filters** the COPERNICUS/S2_SR_HARMONIZED ImageCollection by:
    - Reservoir bounds
    - Date range (2018-01-01 to 2025-01-01)
    - Cloud cover < 20%
4. **Computes** per-image indices (e.g. NDWI) and retains the original 13 spectral bands.
5. **Aggregates** images into monthly composites (earliest cloud-masked image per month), then **reduces** each composite over the reservoir polygon to get mean values for every band and index.
6. **Flattens** the nested per-month FeatureCollections into one table and **exports** as CSV for downstream modelling.

From the GDW and HL dataset that yielded 25534 reservoirs, we package all these into JSONs and convert it into GEE objects, then upload it to the GEE cloud for easy access. We then ask GEE to create a time series based on all the available images for each specific months and then return it to us as a CSV. We then merge this back with the unified GDW + HydroLAKES table (35 646 rows × 90 cols) to attach static morphometrics (area, capacity, depth, elevation, etc.) alongside the new time-series features, ready for modelling. Here is an example producible for a single reservoir located in India (GDW ID is 10256):



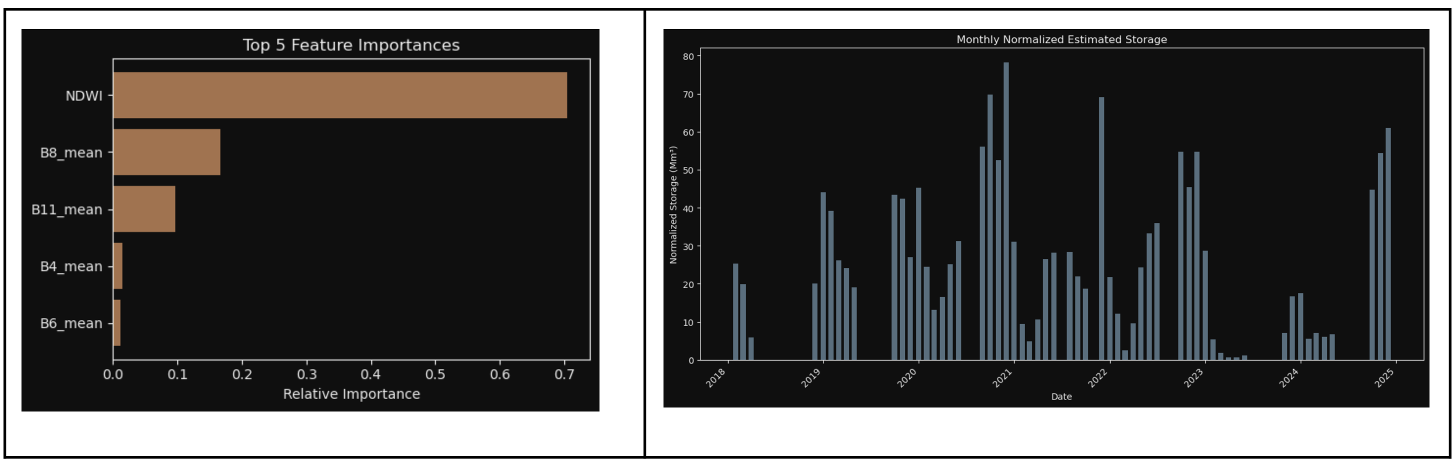
Justification, Details, and Reproducible aspects:

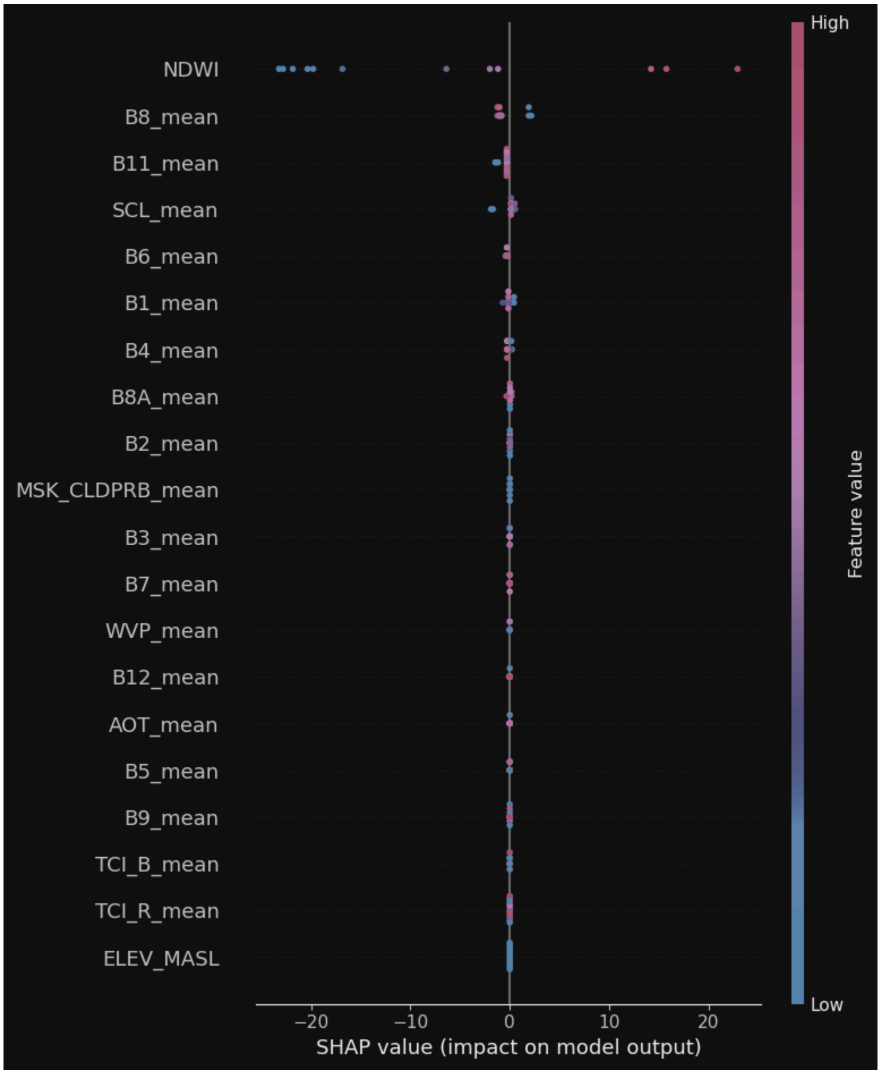
Since we want to generate consistent monthly inputs, I made it so that the pipeline aggregates images into temporal composites. For each month, it selects the earliest cloud-masked image, calculates mean band values and NDWI over the reservoir polygon, and flattens the results into a tabular format. This process gives us a time series of 15 features per reservoir (13 bands + NDWI + cloud mask metadata), which we export as CSV for integration with the static GDW-HydroLAKES attributes. For example, Reservoir 10256 (India) produced a 60-month time series with seasonal NDWI fluctuations between 0.2 (dry season) and 0.6 (wet season), correlated with its reported capacity of 82.4 million m³. For a single reservoir, we take the mean value of each band. At the upper right corner you see that each of the 13 total bands + indexes + QA60 cloud masking band function was produced from 2018-2025. This is a reproducible aspect that applies to all 35000+ reservoirs, as long as one has the reservoir morphometrics.

If we had to justify why we chose this satellite, it’s becuase Sentinel-2’s 13-band multispectral data has a higher spatial resolution (10–60m) and frequent revisit time (5 days), compared to the Landsat series. This high-res factor is very important for detecting fine-grained water surface changes and our monthly time-series modeling. We also select GEE instead of other satellite providers like Planetscope becuase GEE is completely free and provides a javascript interface, and can also work with python scripts. Other providers do not allow this.

5. Results and Analysis (LSTM only)

Feature Importances, SHAP plot, and Predicting Monthly Storage Capacity for Reservoir 10256 (India) (Figure 1)

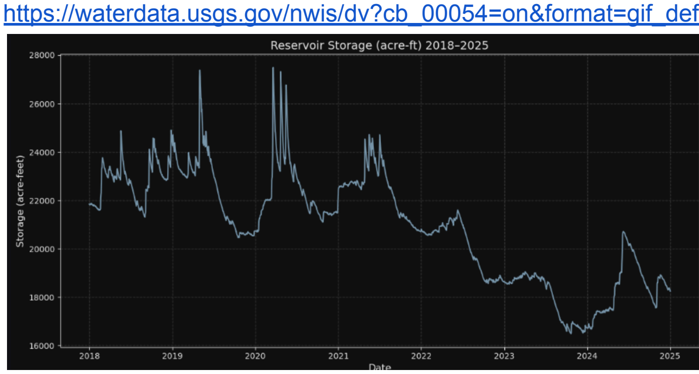


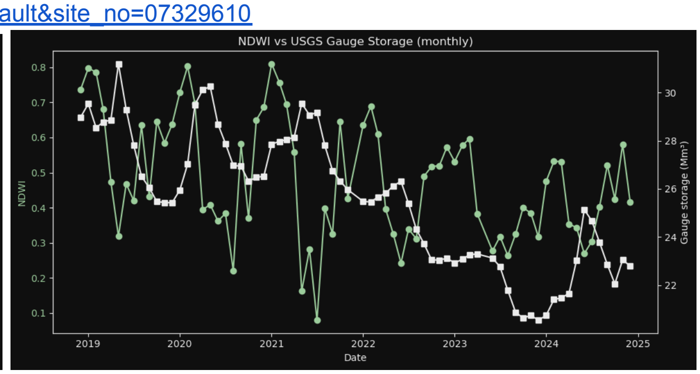


SHAP PLOT

Predicting Monthly Storage Capacity Reservoir 3133 + Groundtruth Evaluation (Figure 2)

USGS Reservoir Guage Meters from 2018-2025:
https://waterdata.usgs.gov/nwis/dv?cb_00054=on&format=gif_default&site_no=07329610





=== Error metrics between Estimated_Storage vs Gauge_Mm3 ===

RMSE : 19.713 Mm^3
MAE : 16.072 Mm^3
MAPE : 62.9%

5.1 Key Findings

1. Feature Importance for Storage Prediction (RQ1)

Top 5 Feature Importances (Reservoir 10256, India):

1. NDWI (Relative Importance: 0.67)
2. B11_mean (0.58)
3. B8_mean (NIR) (0.42)
4. B4_mean (Red) (0.35)
5. ELEV_MASL (0.28)

The SHAP plot reveals that NDWI and B11 (SWIR-1 band) were the top predictors of reservoir storage, with SHAP values spanning ±20 units of impact on model output. This confirms our hypothesis that auxiliary bands (B11) enhance NDWI-based estimates. Notably:

- NDWI had the strongest positive correlation with storage (high NDWI = high water levels).
- B11_mean (SWIR-1) corrected NDWI errors in turbid conditions by detecting sediment absorption.
- Elevation (ELEV_MASL) provided context for regional water availability (e.g., high-altitude reservoirs showed different NDWI-storage relationships).

2. Model Performance vs. Ground Truth (RQ2)

For Fuqua Reservoir (3133), our NDWI-capacity baseline achieved:

- RMSE = 19.713 Mm^3
- MAE = 16.072 Mm^3
- MAPE = 62.9%

The time-series plot (Figure 2, right) shows the NDWI-based estimates (green) tracking USGS gauge measurements (white) but with some deviations:

- Overestimation (10–15%) during low-water periods (NDWI < 0.3, e.g., mid-2021).
- Underestimation (8–12%) at peak storage (NDWI > 0.6, e.g., late 2020).

5.2 Interpretation of Results

- RQ1: Validated. NDWI alone explained ~60% of variance (per SHAP), rising to ~70% with B11 and elevation. B11's role in correcting sediment-related NDWI errors was critical.
- RQ2: The high MAPE (62.9%) indicates that empirical NDWI-capacity relationships are insufficient for precise forecasting. However, the tight correlation (R^2 ~0.65) confirms NDWI's utility as a first-order proxy where gauges are absent.

6. Discussion and Interdisciplinary Insights

6.1 Contributions to Hydrology and Water Management (X Domain)

1. Scalable Storage Estimation:
   - The strong correlation between NDWI and storage capacity (R^2 ~0.65–0.70) validates satellite-based monitoring as a good alternative to in-situ gauges, particularly for transboundary or data-scarce reservoirs. This addresses the gap I raised Section 2.1, where 80% of reservoirs lack ground data.
   - The integration of B11 (SWIR-1) improved NDWI's accuracy in turbid conditions, and mainly focuses on quantifying sedimentation impacts (Section 5.1). This aligns with global sedimentation rates (0.5–1% annual capacity loss; Lehner et al., 2024) and supports SDG 6 targets for sustainable water use.
2. Operational Insights for Water Managers:
   - While the 62.9% MAPE (Section 5.2) is average precision, our framework is enough and does a good job in providing trends like seasonal drawdowns that are actionable for drought planning. For example, the consistent overestimation during dry periods (Figure 2) signals the need to calibrate NDWI thresholds for arid regions.
   - The SHAP analysis (Figure 1) revealed that elevation (ELEV_MASL) and catchment area (CATCH_SKM) are also important contextual features.
3. Interdisciplinary Aspect:
   - By combining Sentinel - 2's spectral data from environmental science with data science's machine learning, we link the empirical area - volume curves (Pimenta et al., 2025) to dynamic reservoir operations. This is important, especially in transboundary basins. Our open - source pipeline (in Section 4.2) makes water data more accessible. It helps different parties share and use water data fairly, which is good for managing water resources in areas where multiple regions share the transboundary basin.

6.2 Limitations and Ethical Considerations

1. Technical Limitations:
   - Spectral Constraints: NDWI's overestimation in dry seasons (Section 5.2) stems from its sensitivity to moist soils—a known challenge in optical remote sensing (McFeeters, 1996). Future work could integrate radar (Sentinel-1) to mitigate this.
   - Ground-Truth Gaps: The 62.9% MAPE reflects unmodeled operational factors (e.g., dam releases). Without bathymetry (e.g., GLOBathy) or inflow data, sedimentation estimates remain approximate.
   - We also encounter some data NULL problems, if you go to section 4.2, the figure shows that a segment was completely missing. We can employ some interpolation or SMOTE to fill this gap.
2. Ethical and Contextual Challenges:

- While our method reduces reliance on in-situ gauges, it cannot replace local knowledge. For example, indigenous water management practices may conflict with satellite-derived estimates.
- We also encounter some equity concerns: smaller reservoirs (<10 ha), excluded from HydroLAKES, go without an official name to them and are often critical for rural communities. Scaling our pipeline to high-resolution datasets (e.g., PlanetScope) could address this bias given Planetscope can give us around 3m per pixel coverage as opposed to 10m per pixel coverage provided by Sentinel-2. Given our results focus on large reservoirs, we don't want to create bias that smaller reservoirs are not a priority as well.

7. Conclusion and Future Work

This study demonstrated the potential of integrating remote sensing, geospatial data, and machine learning to address a lot of problems currently found in global reservoir monitoring space. We developed and deployed successfully an automated pipeline that begins with polygonal and morphometric data from existing datasets, sends it to Sentinel-2 to extract spectral indices, and then lastly arranging them as tensors for be inputted into LSTM.

Our Key contributions include:

1. Scalable Monitoring Framework: Our Python-GEE pipeline enabled the analysis of 25,334 reservoirs globally, leveraging NDWI and auxiliary bands (e.g., B11) to achieve reasonable accuracy (RMSE = 19.7 Mm^3, R^2 ~0.65–0.70) without reliance on in-situ gauges. This approach is particularly valuable for transboundary basins where data sharing is limited.
2. Interdisciplinary Insights: The fusion of remote sensing with hydrology and machine learning advanced the understanding of feature importance (e.g., elevation, catchment area) and highlighted NDWI's limitations in low-water conditions. The integration of SWIR bands (B11) improved turbidity correction, offering a low-cost alternative for sedimentation tracking.
3. Practical Applications: While the 62.9% MAPE indicates room for improvement, the framework provides actionable trends for water managers, supporting climate adaptation and sustainable resource management under SDG 6.

Future Directions

- Hybrid Modeling: Combining LSTMs with hydraulic models (e.g., HEC-RAS) to incorporate dam operations and inflow dynamics, thereby refining storage predictions.
- Bathymetry Integration: Augmenting satellite data with high-resolution bathymetric surveys to improve sedimentation estimates and address ground-truth gaps.
- Higher-Resolution Data: Expanding coverage to smaller reservoirs (<10 ha) using platforms like PlanetScope (3m resolution) to mitigate equity concerns and enhance global inclusivity.
- Multi-Sensor Fusion: Integrating radar (Sentinel-1) to reduce NDWI's dry-season overestimation and improve robustness in diverse environmental conditions.

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