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From Sediment to Storage: Tracking the World's Reservoirs

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Abstract

From Sediment to Storage: Tracking the World's Reservoirs

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Reservoirs formed by dams underpin global water, food, and energy security, yet their long-term viability is increasingly threatened by sedimentation — the gradual infilling of storage capacity by deposited sediment. Despite its importance, the magnitude, spatial variability, and temporal evolution of sediment-driven storage loss remain poorly quantified at global scale, constrained by sparse observations and the absence of scalable monitoring frameworks. This dissertation asks a fundamental question: **how much reservoir storage capacity remains worldwide, and how rapidly is it being lost?**

To answer this, the research develops an integrated framework combining satellite remote sensing, hydrological modeling, machine learning, and curated field observations. Reservoir monitoring is first advanced through RAT 3.0 (Reservoir Assessment Tool), a scalable open-source system that estimates key reservoir dynamics — inflow, outflow, evaporation, storage change, and surface area — from satellite observations alone. Delivered as a Python library with full documentation and continuous integration, RAT 3.0 is designed for broad accessibility and reproducibility.

The observational foundation is strengthened by GRILSS (Global Reservoir Inventory of Lost Storage by Sedimentation), a new open-source dataset compiling sedimentation rates and storage loss for over 1,000 reservoirs across major river basins worldwide. Building on GRILSS, a machine learning model — RECLAIM (Reservoir Estimation of Capacity Loss using AI-based Methods) — estimates sedimentation rates by integrating multi-decadal Earth observations with hydroclimatic and geomorphic predictors, achieving an R^2 of 0.86, RMSE of 4.44 MCM/year, and MAE of 1.65

MCM/year. Critically, RECLAIM enables global-scale estimation without reliance on costly repeated bathymetric surveys.

These components converge in GLoRS (Global Long-term Reservoir Sedimentation), the first multi-decadal, observationally constrained assessment of global reservoir sedimentation spanning 1984–2023. Major reservoirs are losing storage at approximately 0.42% per year on average, with nearly one-fifth of capacity already lost across typical large reservoirs. Sedimentation patterns are spatially organized and temporally dynamic, driven by hydroclimatic controls that intensify deposition during extreme events.

Together, these tools and datasets transform reservoir sedimentation from a localized, data-scarce problem into a globally observable and quantifiable phenomenon. This work provides a foundation for identifying the most vulnerable reservoirs, designing targeted sediment management strategies, and supporting resilient water infrastructure planning in the face of a changing climate.

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DEDICATION

To my parents, Mr. Sanjay Minocha and Mrs. Nalini Minocha, and my brother, Mr. Arpit Minocha.

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Chapter 1. Introduction

Artificial reservoirs, created through the construction of dams across rivers, have become foundational to modern water resource systems. Over the past century, they have enabled societies to regulate highly variable natural hydrological processes, transforming water into a managed and reliable resource. Today, reservoirs support irrigation, domestic and industrial water supply, hydropower generation, and flood mitigation, forming the backbone of water, food, and energy security worldwide (McCully, 1996). The rapid expansion of dam infrastructure reflects this importance; global dam construction has increased nearly ten-fold over the past seven decades, with more than 63,000 large dams now regulating river systems across the planet (ICOLD, 2025). Figure 1.1 shows the geographic location of few thousand major reservoirs around the world. Hereafter in this dissertation, the terms dam and reservoir will be used interchangeably as shorthand for the dam-reservoir system.

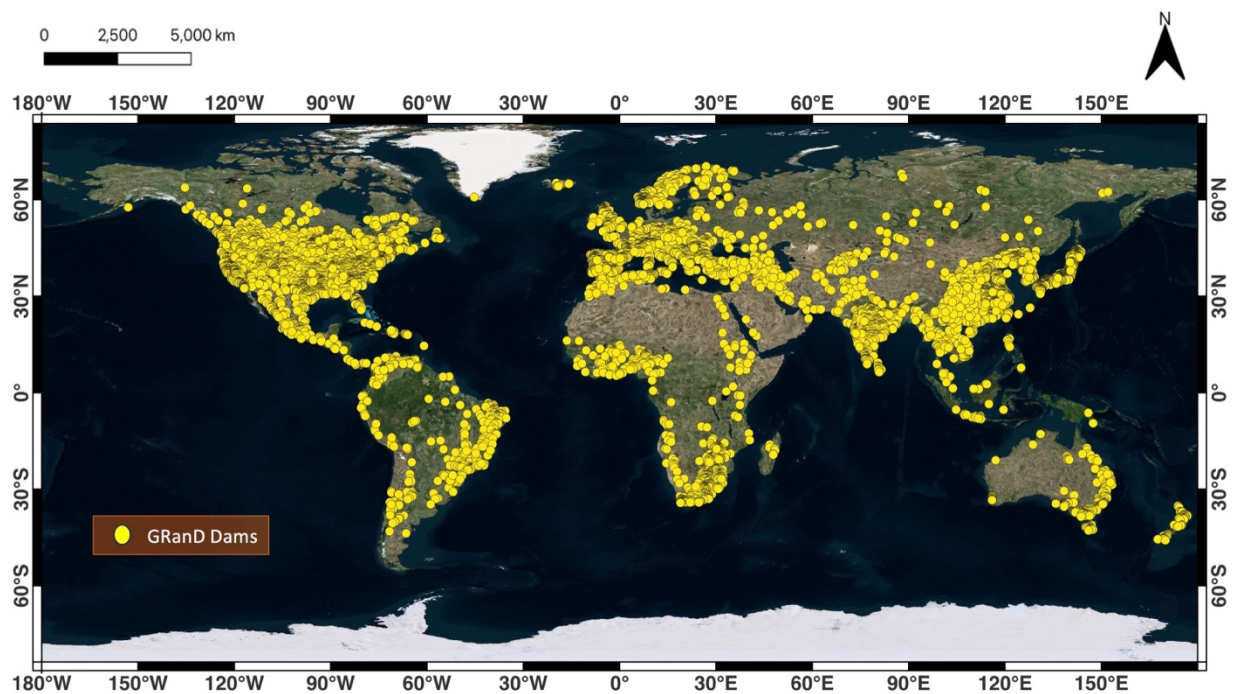


Figure 1.1 Geographic representation of major dams around the world derived from a global dam database known as GranD (Lehner et al., 2011)

This expansion has been driven by growing population, urbanization, industrialization, and agricultural intensification, all of which have increased demand for reliable freshwater resources

(Chen et al., 2016). By storing water during wet periods and releasing it during dry periods, reservoirs effectively buffer climatic variability and enable stable water supply systems. In addition, reservoirs contribute significantly to renewable energy production through hydropower, often considered a lower-carbon alternative to fossil fuels (Li and He, 2022).

However, despite these benefits, dams fundamentally alter natural river systems and introduce a wide range of environmental and ecological consequences. These include disruption of sediment transport, alteration of downstream flow regimes, habitat fragmentation, loss of biodiversity, changes in water temperature and chemistry, and barriers to fish migration (Nguyen et al., 2024; Tundisi, 2018; Wu et al., 2019 and Pelicice et al., 2015). Reservoirs also influence biogeochemical cycles and can contribute to greenhouse gas emissions under certain conditions (Tran et al., 2023). As a result, dams represent one of the most significant anthropogenic modifications to the Earth's hydrological and ecological systems.

Given this dual role—providing essential services while introducing environmental challenges—there is a critical need to monitor reservoir systems effectively. Monitoring enables not only the safe operation of dams but also the optimization of water allocation, energy production, and flood control. Traditionally, reservoir monitoring has relied on in-situ measurements such as gauges, flow meters, and bathymetric surveys. While accurate, these methods are often expensive, labor-intensive, and spatially limited, making them impractical for large-scale or global monitoring efforts (Campbell, 2009 and Beckers et al., 2018). Furthermore, data availability is often restricted due to political, logistical, or institutional barriers, particularly in transboundary river basins where shared water resources complicate data exchange (Hossain et al., 2023).

1.1. Emergence of Satellite Remote Sensing for Reservoir Monitoring

Over the past two decades, satellite remote sensing has emerged as a transformative tool for monitoring inland water systems. Unlike traditional approaches, satellite observations provide consistent, repeatable, and spatially extensive measurements of Earth's surface, enabling monitoring at regional to global scales (Bonnema et al., 2021 and Dutta, 2016). Remote sensing allows for the observation of key reservoir variables such as surface water extent and, in some cases, water elevation, which together can be used to infer storage dynamics.

Satellite-based monitoring offers several advantages. First, it provides near real-time observations, enabling timely decision-making during extreme events such as floods and droughts. Second, it enables monitoring in data-sparse or politically sensitive regions where ground-based observations are unavailable. Third, it allows for the consistent analysis of long-term trends across large numbers of reservoirs, which is critical for understanding global water system dynamics.

Despite these advantages, satellite-based approaches also face limitations. Most satellite missions provide either water surface area (e.g., optical sensors) or water elevation (e.g., radar altimetry), but rarely both simultaneously. Estimating reservoir storage requires combining these variables with bathymetric information, typically represented through area–elevation–volume relationships. Digital elevation models (DEMs), such as SRTM, are often used to approximate reservoir bathymetry; however, they represent static topography and do not account for sediment accumulation over time. As a result, storage estimates derived from such approaches may significantly overestimate the true available capacity of reservoirs.

The recent launch of the Surface Water and Ocean Topography (SWOT) mission represents a major advancement in this field, as it enables simultaneous measurement of water surface elevation and extent (Bonnema and Hossain, 2019). However, even with such advancements, a fundamental challenge remains: the inability to account for sedimentation-driven changes in reservoir storage.

1.2. The Global Challenge of Reservoir Sedimentation

Reservoir sedimentation is a pervasive and irreversible process whereby sediments transported by rivers settle within reservoirs, gradually reducing their storage capacity. While reservoirs are designed to store water, they also act as sediment traps, interrupting natural sediment transport processes and leading to accumulation within the reservoir as shown in Figure 1.2 (Schleiss et al., 2016).

This process has significant implications for the long-term sustainability of water infrastructure. As sediment accumulates, reservoirs lose their effective storage capacity, reducing their ability to supply water, generate hydropower, and mitigate floods. Sedimentation can also impair dam operations by clogging intakes, reducing turbine efficiency, and increasing maintenance costs (Brandt, 2000; Adamo et al., 2021; Kondolf et al., 2014 and Wisser et al., 2013).

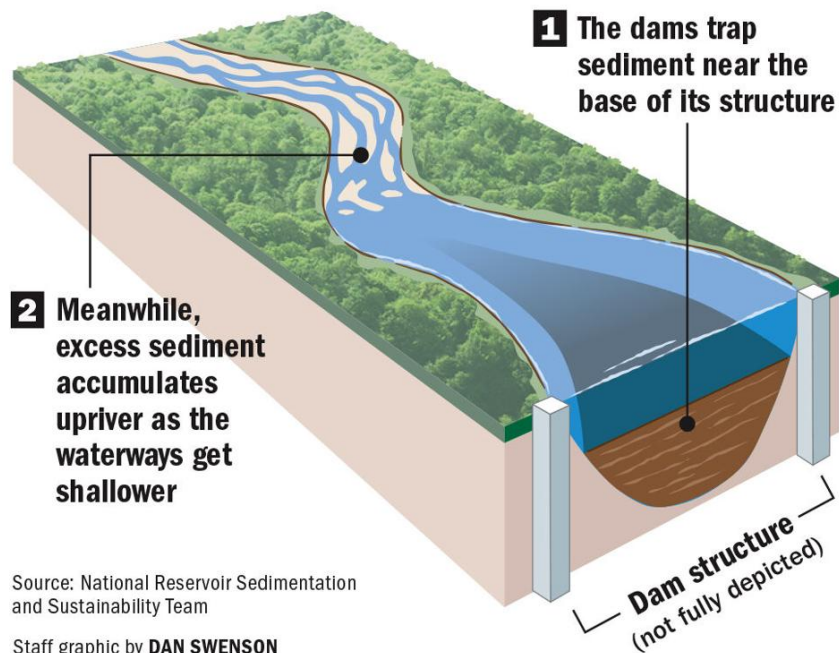


Figure 1.2 Schematic of sedimentation in reservoirs showing inflow sediment deposition
(Das et al., 2022)

At a global scale, the impact of sedimentation is already evident. Studies suggest that global reservoir capacity peaked around the early 2000s and has since stagnated or declined, despite continued dam construction. Between 1987 and 2010, global per capita reservoir storage decreased by approximately 19%, and when sedimentation is considered, the decline increases further (Wisser et al., 2013). These trends highlight a paradox: although more dams are being built, the usable storage they provide is not increasing proportionally.

The implications of this decline are profound. Reduced storage capacity limits water availability for agriculture, energy production, and domestic use, while also diminishing the ability of reservoirs to buffer hydrological extremes. In a changing climate characterized by increasing variability in precipitation and runoff, this loss of storage capacity poses a significant risk to global water security.

1.3. Limitations of Current Sedimentation Assessment Approaches

Despite its importance, reservoir sedimentation remains poorly quantified at global scales. Existing methods for estimating sedimentation can be broadly categorized into direct and indirect approaches.

Direct methods, such as bathymetric surveys and sediment core sampling, provide highly accurate estimates of storage loss but are costly, labor-intensive, and difficult to repeat frequently across large numbers of reservoirs (Furnans & Austin, 2008). As a result, only a small fraction of reservoirs worldwide have been surveyed, and even fewer have long-term records of sedimentation.

Indirect methods, including numerical modeling and remote sensing–based approaches, offer more scalable alternatives but rely on assumptions or data that are often unavailable and are time consuming. Numerical models require detailed information on watershed characteristics, sediment transport processes, and hydrological conditions, while remote sensing approaches often depend on long-term, consistent observations of water levels and surface area (Ghosh et al., 2024 and Hanmaiahgari et al., 2018).

Furthermore, sedimentation rates are highly variable in space and time, influenced by factors such as land use, climate variability, reservoir operations, and watershed characteristics. This variability makes it difficult to generalize findings from localized studies to global scales.

A major limitation in advancing global understanding of reservoir sedimentation has been the absence of a comprehensive, well-curated dataset of observed sedimentation rates. While some national-level datasets exist, there has historically been no unified global database capturing sedimentation and storage loss across reservoirs worldwide (Syvitski et al., 2003 and Vanmaercke et al., 2011).

1.4. Bridging the Data Gap: Toward Scalable Monitoring and Modeling

Recent advances in Earth observation, hydrologic modeling, and data science have created new opportunities to address long-standing challenges in reservoir monitoring and sedimentation assessment. Multi-decadal satellite archives now provide repeated observations of hydrological variables at regional to global scales, while improvements in computational methods make it

increasingly feasible to integrate remote sensing, physical models, and data-driven approaches within scalable frameworks.

Among the few existing efforts in this direction, the Reservoir Assessment Tool (RAT) demonstrated the potential of combining satellite remote sensing with hydrological modeling to estimate key components (Figure 1.3) of a reservoir's dynamic state, including inflow, outflow, storage change, evaporation, water surface area, and water elevation (Biswas et al., 2021 and Das et al., 2022). Earlier versions of RAT provided an important proof of concept that reservoir operations could be inferred in a satellite-driven and assumption-light manner. However, these early versions also revealed important limitations. Their broader operational use remained constrained by issues of scalability, reproducibility, ease of installation, robustness to data gaps, and accessibility for non-expert users. Thus, while RAT established an important foundation, a major gap remained in translating such a framework into a truly open, robust, and globally deployable tool for the wider water management community.

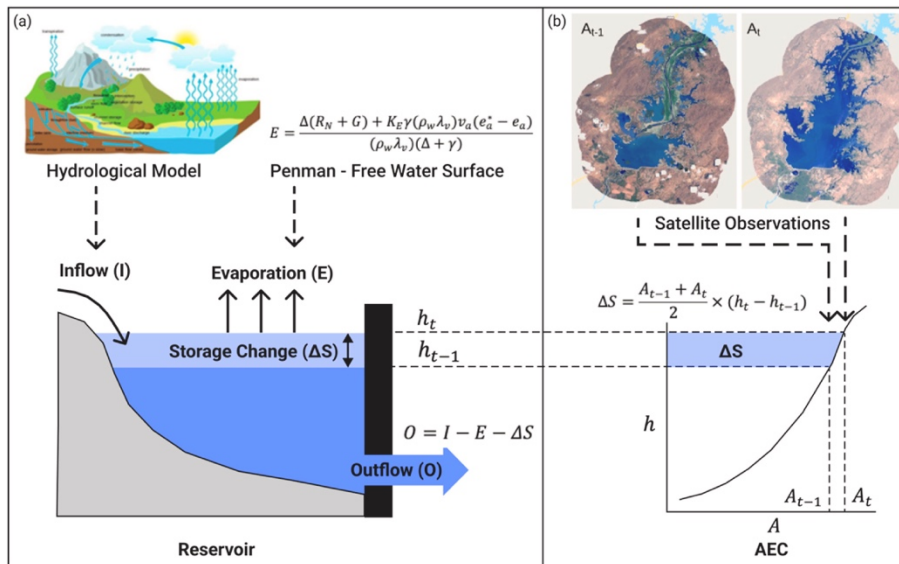


Figure 1.3 RAT conceptual framework showing inflow, outflow, evaporation and storage change (Das et al., 2022)

A second and even more fundamental limitation lay in the absence of a globally curated observational dataset on reservoir sedimentation and storage capacity loss. Although sedimentation is widely recognized as one of the most consequential threats to reservoir sustainability, published observations remain scattered across reports, journal articles, agency

documents, and regional databases, often in inconsistent formats and with incomplete metadata (Schleiss et al., 2016). This lack of a unified and public archive has severely constrained comparative analyses across regions and has also prevented the development of globally scalable predictive approaches.

A third major gap concerned modeling capability itself. Even with expanding Earth observation records, there existed no globally scalable data-driven framework specifically designed to estimate reservoir sedimentation and capacity loss by integrating observed sediment records with multi-decadal satellite and hydroclimatic data. Most prior studies remained local or regional, relied on simplified assumptions, or could not generalize across diverse climatic and geomorphic settings (Tan et al., 2025; Cox et al., 2024 and Giri et al., 2021). Therefore, the field lacked not only the observational database needed to train such models, but also the predictive framework needed to translate fragmented observations into spatially extensive and temporally resolved estimates of sedimentation.

This dissertation is motivated by the need to bridge all three of these gaps in sequence. First, reservoir dynamics must be monitored through a scalable and accessible system, which motivates the development and advancement of RAT 3.0 as an open and operational software platform. Second, sedimentation observations must be systematically assembled into a unified global inventory, which motivates the development of GRILSS (Global Reservoir Inventory of Lost Storage by Sedimentation). Third, those observations and satellite-derived predictors must be translated into a predictive, globally scalable framework, which motivates the development of RECLAIM (Reservoir Estimation of Capacity Loss using AI based Methods). Together, these components form the methodological foundation necessary to move from fragmented local knowledge toward a global and time-varying understanding of reservoir capacity decline.

1.5. Research Gap and Motivation

Despite the essential role of reservoirs in global water, food, and energy systems, a fundamental question remains unresolved:

How much global reservoir storage capacity remains, and how rapidly is it being lost due to sedimentation?

This question sits at the center of this dissertation. Answering this question is essential for prioritizing reservoirs at risk of rapid capacity loss, guiding sediment management investments, and informing long-term planning for water security, hydropower reliability, and flood resilience under increasing hydroclimatic variability.

However, this question remains difficult to address due to fundamental limitations in current understanding and infrastructure. Existing global assessments of reservoir sedimentation are largely based on sparse regional datasets, fixed long-term rates, or simplified assumptions that fail to capture the spatial variability and temporal evolution of sedimentation processes (Gonzalez et al., 2023; Wisser et al., 2013 and Perera et al., 2023). As a result, they provide limited insight into how storage loss is progressing today or where it is accelerating.

More importantly, the challenge is not only one of data scarcity but of missing capability. There has been no scalable and accessible framework for monitoring reservoir dynamics across large numbers of systems, no consistently curated global inventory of observed sedimentation and storage loss, and no predictive approach capable of translating fragmented observations into time-resolved estimates of capacity decline.

These limitations highlight that the central question cannot be addressed directly with existing tools and data. Instead, it requires a coordinated advancement in monitoring, data curation, and modeling to enable a global and time-varying understanding of reservoir sedimentation.

1.6. Objectives and Scope of the Dissertation

This dissertation aims to address these gaps by developing a comprehensive, scalable, and data-driven framework for monitoring and estimating reservoir storage dynamics and sedimentation, with the goal of resolving how much storage remains and how rapidly it is being lost. The objectives of this research are:

1. To develop and operationalize scalable tools for monitoring reservoir dynamics using satellite remote sensing and hydrological modeling.
2. To compile and curate a global dataset of reservoir sedimentation and storage loss.

3. To develop a machine learning framework for estimating sedimentation and capacity loss across diverse hydroclimatic and geographic settings.
4. To provide a global, multi-decadal assessment of reservoir storage decline and its spatial and temporal variability.

By integrating these components, this work moves beyond static or localized assessments to provide a time-resolved and globally consistent characterization of reservoir sedimentation. It enables:

- Quantification of remaining usable storage capacity across major reservoirs worldwide
- Identification of rates and hotspots of storage decline
- Resolution of the spatial organization and temporal variability of sedimentation processes
- Evaluation of the sensitivity of sedimentation dynamics to climate and watershed conditions

The resulting Global Long-term Reservoir Sedimentation (GLoRS) dataset establishes, for the first time, a reproducible and scalable framework for diagnosing sediment-driven storage loss across the world's reservoir systems. In doing so, this dissertation advances the understanding of reservoir sedimentation from a localized, data-limited problem to a globally observable and dynamically evolving phenomenon.

More broadly, this work provides a foundation for reassessing the reliability of dam infrastructure, prioritizing reservoirs most vulnerable to capacity loss, and supporting data-driven water resource management under changing climate conditions.

1.7. Broader Impact

Ultimately, this research aims to democratize access to reservoir information and empower stakeholders—from policymakers and water managers to researchers and local communities—with actionable insights. By transforming fragmented data into accessible tools and datasets, this work lowers the barrier to understanding reservoir behavior at scales ranging from individual basins to the global system.

Such capability is critical in a world where water systems are increasingly stressed by population growth, infrastructure aging, and climate variability. By enabling consistent, large-scale monitoring and diagnosis of reservoir dynamics, this work supports more informed decision-making, improved water resource management, and enhanced resilience to hydrological extremes.

In doing so, it contributes to a broader vision: leveraging the vantage point of space and the power of data science to ensure the sustainable management of one of humanity's most critical resources—water.

Chapter 2. Reservoir Assessment Tool Version 3.0: A Scalable and User-Friendly Software Platform to Mobilize the Global Water Management Community

Note: This chapter has been published in its current form in *Geoscientific Model Development*. The only differences are in the numbering of figures, tables, and references to other sections. [Publication: Minocha, S., Hossain, F., Das, P., Suresh, S., Khan, S., Darkwah, G., Lee, H., Galelli, S., Andreadis, K. and Oddo, P., 2024. Reservoir Assessment Tool version 3.0: a scalable and user-friendly software platform to mobilize the global water management community, *Geosci. Model Dev.*, 17, 3137–3156. <https://doi.org/10.5194/gmd-17-3137-2024>]

2.1. Abstract

In the modern world, dams and the artificial reservoirs behind them serve the increasing demand for water across diverse needs such as agriculture, energy production, and drinking water. As dams continue to proliferate, monitoring water availability influenced by reservoir operations is now of paramount importance. The Reservoir Assessment Tool (RAT) is a data-driven software that integrates satellite remote sensing with hydrological models, enabling the estimation of key reservoir parameters such as inflow, outflow, surface area, evaporation and storage changes. The earliest version of RAT (version 1.0) was set up for 1598 reservoirs around the world with limitations in functional robustness, updating frequency and scalability. Some of these limitations on updating frequency and functional robustness were addressed in version 2.0 that was later made operational for the inter-governmental agency of the Mekong River Commission. Recognizing the need for scalability to mobilize the global water management community to benefit from satellite remote sensing, we hereby introduce RAT version 3.0. This version is optimized for accelerating open collaboration among users for continuous improvement and customization of RAT to enable reservoir management breakthroughs. RAT 3.0 represents a wholesale overhaul from the previous versions to empower the global community of users and developers in the spirit of the open-source movement. RAT 3.0 allows reservoir monitoring advancements and new functional developments that can be freely exchanged and seamlessly integrated for continuous evolution of the software. A centralized web application has also been established to facilitate the storage and dissemination

of global reservoir monitoring information along with comprehensive training resources. RAT 3.0 aspires to bridge the traditional practices of water management community with the capabilities of satellite remote sensing. The global impact of the software can be expected to increase as uptake spreads, enabling a more sustainable and equitable utilization of our planet's water resources.

2.2. Introduction

Over the past seven decades, the number of large dams constructed globally to manage water for various purposes, has increased 10-fold, with the current count exceeding 58,700 (ICOLD, 2020). Figure 2.1 provides a geographic representation of the major dams, revealing the extensive presence of dams around the world (Lehner et al., 2011). This increase in the number of dams is a direct result of the growing demand for water resources (Gleick, 2012), which is driven by population growth, urbanization, industrialization, and increasing irrigation (Kannan and Anandhi, 2020). Dams create artificial lakes called reservoirs for reliable water storage and an increasing need for irrigation and domestic and industrial water use (Baxter, 1977). From here on, the term ‘reservoirs’ will be used interchangeably with ‘dams’ and also to refer to these artificial lakes. Dams also play a major role in mitigating floods by attenuating river flow (Sordo-Ward et al., 2012) and in generating hydroelectricity, thus providing a cleaner energy alternative (Baxter, 1977; Biswas, 2012).

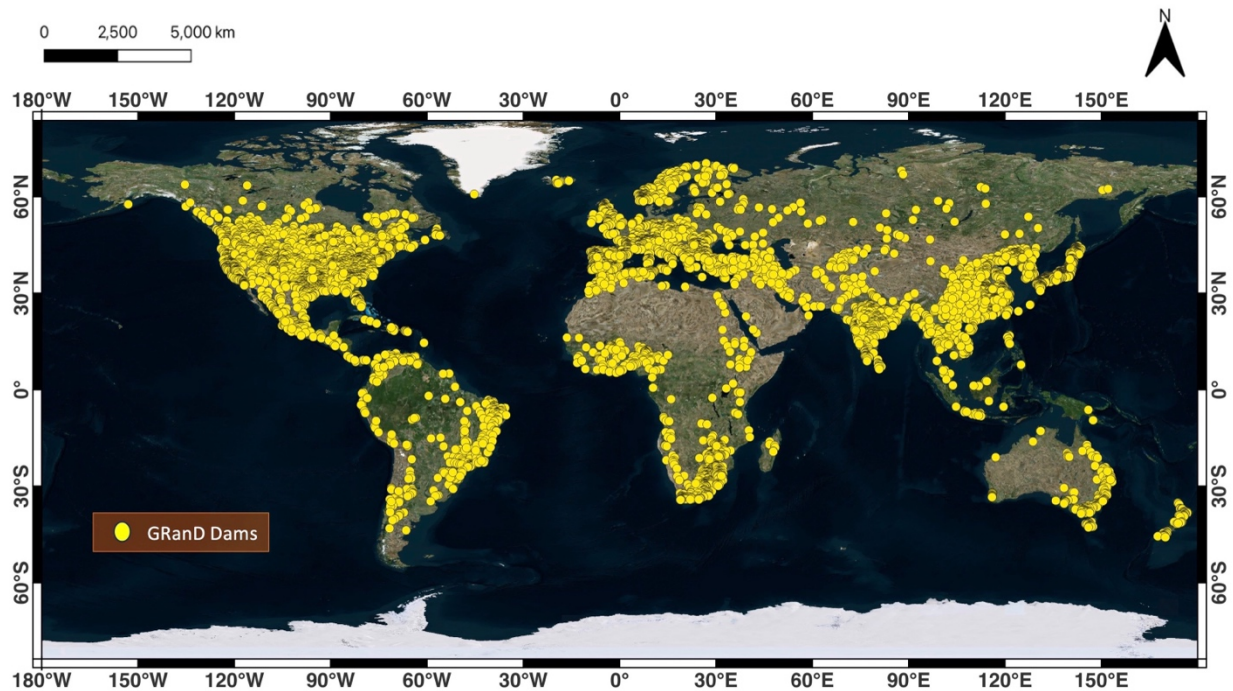


Figure 2.1 Geographic representation of major dams around the world derived from a global dam database known as GranD (Lehner et al., 2011)

While dams have played a crucial role in providing water and energy to communities around the world, they also have a significant number of drawbacks that cannot be ignored. Dams alter downstream water conditions and sediment flow, change water temperatures, and obstruct the movement of organisms and nutrients (Poff and Hart, 2002). As dams disrupt the natural flow of rivers, they can exacerbate drought and flood conditions and negatively impact the aquatic habitat and ecosystem services. This can further affect the livelihoods of people, such as fishermen and farmers.

Given these potential downsides, monitoring dams' performance to ensure safe operation and mitigating negative effects is extremely important. Moreover, monitoring can also help optimize dam operations and maximize its benefits for all stakeholders. Traditional methods of monitoring, such as installing gauges, can be costly and time-consuming as it requires regular maintenance and data collection. In the past few years, satellite remote sensing has emerged as a powerful alternative for monitoring dams because of the wide range of advantages it serves (Bonnema and Hossain, 2017; Bonnema et al., 2021). It allows monitoring at a global scale and provides valuable data on

the aerial extent and elevation of surface water in the reservoirs. These time-varying observations of the reservoir's water condition allow the derivation of storage change. Satellite remote sensing provides near real-time data, making it possible to respond to changes in reservoir conditions in a timely and efficient manner, allowing for more effective management. Remote sensing can also address the issue of limited availability of data on reservoirs and water usage in transboundary river basins, which is often exacerbated by political or logistical barriers (Hossain et al., 2007).

Most studies that analyse the reservoir's dynamic state of storage change and inflow/outflow fluxes using satellite remote sensing are limited to a specific locations or periods (Vu et al., 2021; Bonnema and Hossain, 2017; Zhang et al., 2014). There are also satellite-based reservoir monitoring tools that provide information about reservoir state like water level, but are often restricted in terms of spatial coverage, spatial and temporal resolution, or an exclusive community of expert users. For example, the Global Reservoirs and Lakes Monitor (G-REALM) database, developed by the U.S. Department of Agriculture's Foreign Agricultural Service (USDA-FAS), routinely monitors lake and reservoir height variations every 10 days based on Jason series nadir altimeter data. The Hydroweb database, developed at the LEGOS laboratory (Laboratoire d'Etudes en Géophysique et Océanographie Spatiales) in Toulouse, France, contains time series of water levels over large rivers, lakes and wetlands at the global scale (<http://hydroweb.theia-land.fr/>). Most reservoir monitoring studies or systems that are available today assume simplified operating rules based on reservoir storage capacity rather than the time-varying nature of the reservoir's actual operations driven by changing hydrology (supply) and user needs (demand). In 2021, Biswas et al. (2021) addressed these gaps by introducing an assumption-free and satellite data-driven reservoir monitoring tool called Reservoir Assessment Tool (RAT) version 1.0 (RAT 1.0). This version was later upgraded with a few enhancements by Das et al. (2022) as RAT version 2.0 (RAT 2.0).

RAT helps water managers to track a reservoir's dynamic state comprising inflow, outflow, evaporation, storage change, storage level and extent. RAT 1.0 was operational for 1598 reservoirs worldwide, at a monthly update frequency that was used to generate monthly estimates of reservoirs' dynamic states (Biswas et al., 2021). Readers can still access the outputs of this original version at http://depts.washington.edu/saswe/rat_beta. In RAT 2.0, the updating frequency was

improved to sub-weekly by leveraging data from multiple satellites. RAT 2.0 further enhanced the accuracy of storage change and outflow as Das et al. (2022) devised a more advanced multi-sensor surface water classification technique called ‘TMS-OS.’ RAT 2.0 operations have so far been primarily limited to the Mekong River basin and inter-governmental agency stakeholders, with scalability and reproducibility for the broader water management community remaining unexplored (Das et al., 2022). For an interested user with limited literacy on satellite remote sensing data, operationalizing RAT 1.0 or 2.0 for tracking reservoirs in a river basin of their choice requires significant training.

This chapter describes an improved version of RAT (version 3.0), hereafter termed as RAT 3.0, driven by the need to lower the barrier of entry for first-time users and to improve scalability, robustness and reproducibility. RAT 3.0 is designed to be easy-to-apply and easy-to-operate within an open-source software architecture. Software that is built on these design features can potentially mobilize the global water community to explore, use and improve RAT in the spirit of open-source development similar to Linux development. RAT 3.0 can benefit not only governments, hydrologists, researchers, and stakeholders but also the individual user who relies on water resources for their livelihood, such as farmers, city residents, and fishermen. Access to near real-time information on the reservoir’s dynamic state can empower the individual user or a community by first quantifying any potential negative impact of floods and droughts, preparing for them, and optimally utilizing available water resources. The high frequency operational feature of RAT 3.0 can help farmers make informed decisions on irrigation and crop planning, assist city residents in water conservation efforts and future usage planning, and aid fishermen in identifying the best fishing locations while avoiding areas with low water levels. Additionally, a scalable software like RAT 3.0 can be used to plan and optimize hydroelectricity generation (Chowdhury et al., 2022). These are just some of the many examples of what may be possible when a reservoir monitoring tool is made scalable and easy to operate. Our motivation for developing the RAT 3.0 software is to accelerate breakthroughs in the broader field of managed water resources driven by the grassroots needs of local users worldwide.

The architecture of RAT 3.0 has been designed in such a way that it requires minimal user input with additional flexibility added for the more advanced users. It is more robust and less susceptible

to data gaps or instability that satellite remote sensing systems can sometimes experience. Operational efficiency has also been improved as RAT 3.0 can remember the equilibrium state of the basin at each time step, making the need for model spin up unnecessary in a cron job. The directory structure for major and intermediate outputs of RAT 3.0 has been reorganized for better database management. With this release of RAT 3.0, the conventional water management community can be more empowered with the vantage of space by providing an easy-to-use, scalable software architecture to monitor reservoirs. We believe such a software has the potential to build a self-sustaining community of users who can actively contribute to the continuous improvement and upkeep of the reservoir monitoring software.

2.3. Foundation of Reservoir Assessment Tool (RAT) 3.0

2.3.1. History and Purpose

RAT is a framework that employs satellite-based remote-sensing data and hydrological modeling to estimate the outflow of a reservoir via a mass balance equation. To estimate the inflow, RAT uses meteorological data and hydrological modeling. In RAT 1.0 (Biswas et al., 2021), the hydrological model used was the Variable Infiltration Capacity (VIC) version 4.2.d, which was later replaced with VIC-5 (Hamman et al., 2018) in RAT 2.0 by Das et al. (2022). To compute storage change in a reservoir, two inputs are required: the area elevation curve (AEC) and the change in the surface area or elevation of the reservoir. The AEC is also known as Area-elevation volume (AEV) or hypsometric curves. The AEC curve summarizes quantitatively the bathymetry of the reservoir and helps compute the inundated area of the reservoir for a given storage level or vice versa. Consequently, with two successive satellite observations of water elevation or surface area, the storage change can be derived. In RAT 2.0, the user had to provide the AEC for all reservoirs, which could be retrieved from either in situ pre-dam topographic maps or an available digital elevation model (DEM). The change in the surface area of the reservoir is estimated by observing the alteration in the number of water-classified pixels of the satellite imagery within the reservoir's region of interest. Alternatively, if the reservoir's water surface elevation information is available, such as from nadir-looking radar altimeters, surface area can be estimated from the AEC. The Penman Equation (Penman, 1948) is used in RAT 2.0 to calculate evaporation from a

reservoir, leading to the estimation of reservoir outflow using the mass balance equation (Figure 2.2). Readers are encouraged to refer to Biswas et al. (2021) and Das et al. (2022) for a process-based understanding of RAT. This paper will hereafter focus mostly on the software model development aspect of RAT 3.0.

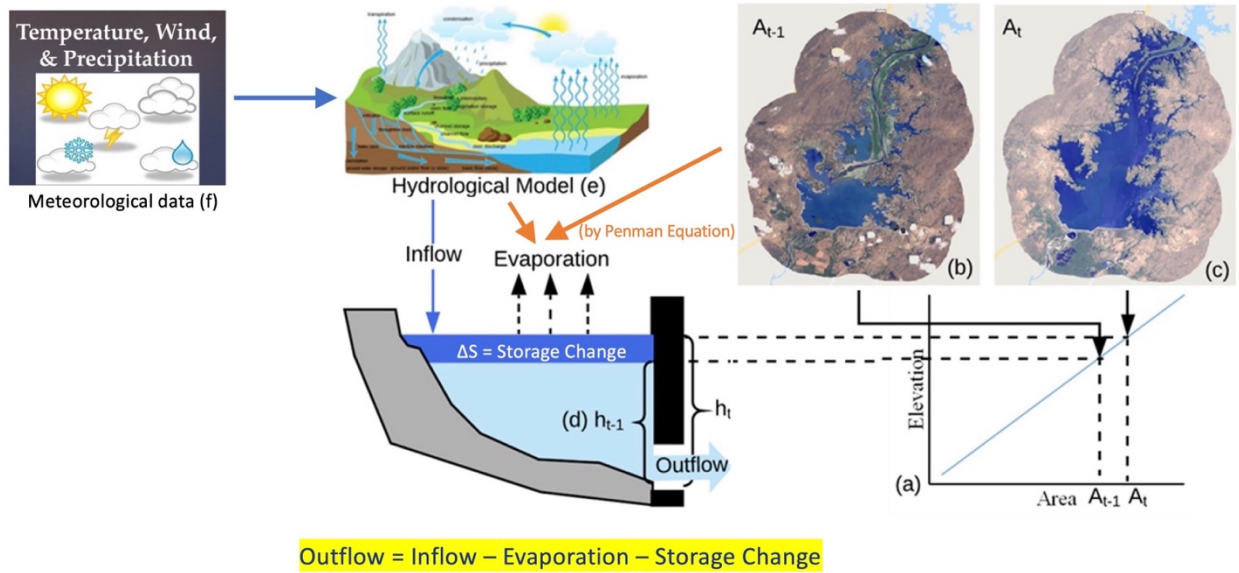


Figure 2.2 Conceptual model of RAT and the mass balance equation.

RAT was developed as a first-of-its-kind reservoir monitoring tool that could remotely monitor the changing dynamics of reservoirs, providing the global community with a comprehensive understanding of how they impact natural river flow. One of its original purposes was to serve as a decision-making tool for forming and evaluating water-sharing agreements between countries in a river basin. Despite the success of RAT 1.0, the monthly frequency of updating for reservoir state, limited its use. Monthly estimates of reservoir outflow and storage fail to capture the operating patterns of a reservoir at finer scales, such as hydropeaking, often required for many decision-making needs of the water manager. RAT 2.0 was therefore developed based on feedback from stakeholders, particularly from member countries of the Mekong River Commission (MRC), to improve the updating frequency (to weekly) and improve the accuracy of outflow data. This resulted in better decision-making for stakeholder agencies. As a result, RAT 2.0 was the first major operational uptake by a large inter-governmental river agency such as the MRC (Das et al, 2022).

2.3.2. Why RAT 3.0?

RAT 3.0 has been developed to expand on the improvements made in the RAT 2.0 framework and apply them on a global scale to achieve RAT's original design goals. The provision of sub-weekly estimates of reservoir outflow can enable the user to gain insight into the operational patterns of dams and their effects on the aquatic environment. RAT 3.0 has been designed to appeal to a broader range of users beyond just government water agencies and large stakeholder communities, using a user-friendly setup that can run locally on any Unix machine for any reservoir worldwide. Input requirements have been significantly reduced in RAT 3.0, making it easier for non-hydrology communities such as stakeholders representing farmers and fishing communities to operate the tool. Wherever possible, familiarity with data and parameters related to hydrologic modelling or remote sensing is not required for the RAT 3.0 user. The open-access, scalable and user-friendly features of RAT 3.0 is designed to nurture a self-sustaining community of users who can actively contribute to the open-source development of the software, leading to further advancements, modifications, and breakthroughs in new frontiers for managing Earth's precious water resources. Figure 2.3 summarizes the technological evolution of RAT from version 1.0 to version 3.0.

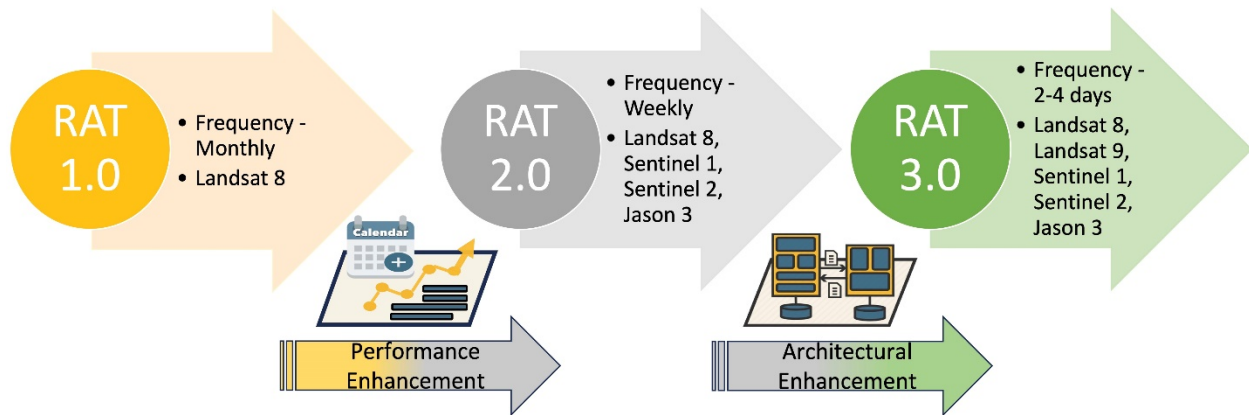


Figure 2.3 Technological evolution of the RAT software from version 1.0 to version 3.0.

Names of key satellite missions are mentioned in the second bullet of each version.

The scalability that is now made structurally inherent in the RAT 3.0 modeling platform can now improve scientific inquiries on reservoir-regulated river systems, their environmental implications and broader sustainability impact. For example, RAT 3.0 can now facilitate the modeling of human-induced alterations to the global water cycle and the evolving climate using digital twin experiments. Today digital twin experiments are the staple currency for scientific attribution studies. These experiments are crucial for scientific attribution studies, particularly in understanding the extent to which alterations in surface water are influenced by human activities versus natural factors, which were earlier difficult to carry out. Now that RAT 3.0 lowers the barrier of entry for global set up under a variety of assumptions and simulated scenarios, the scientific community can easily carry out such digital twin experiments. For example, today with RAT 3.0, one can have two versions of global climate model running, one that uses RAT to model the world's dams and one without modelling dams; or two versions of RAT, one assimilating latest satellite data and other not. There can also be other digital twin experiments that can be used for evaluating diverse elements such as satellite missions, Digital Elevation Models (DEMs), and hydrological models. As an illustrative example, consider the application of RAT to model reservoir parameters in two scenarios, one integrating data from the recently launched Surface Water and Ocean Topography (SWOT) satellite mission and the other excluding such data. RAT can be used to investigate and quantify how much benefit do such new scientific satellite missions bring to improve our understanding of the state of the art.

Such digital twins allow convenient scientific breakthroughs in delineating attribution, meeting the essential requirements of the scientific community engaged in environmental stewardship. This clearly represents one of the key underlying scientific motivations behind development of RAT 3.0.

Another distinctive strength of RAT 3.0 lies in its capacity to generate historical and contemporary data for various reservoir parameters, including inflow, outflow, and evaporation. This capability enhances our understanding of the intricate relationships between these parameters and other environmental variables. By exploring global-scale correlations, such as greenhouse gas emissions versus storage change, downstream river temperature versus outflow, and fish count versus water

elevation, RAT 3.0 enables comprehensive studies and testing of hypotheses. Additionally, the copious data produced by RAT can be leveraged to forecast extreme events, such as floods, thereby contributing to proactive and effective risk management. Therefore, with the release of RAT 3.0, we anticipate catalyzing the scientific community's efforts to address the identified knowledge gaps, thereby advancing our understanding of reservoirs and their intricate dynamics.

2.3.3. The Framework of RAT 3.0

The RAT 3.0 framework comprises 14 key steps that need to be executed successfully to complete a RAT installation run (Figure 2.4). While these steps are independent in their execution, some of them may depend on others for input. For example, outflow calculation requires the prior execution of inflow estimation through VIC and its streamflow routing. Hence, users must ensure that any omitted step has already run or that its output does not serve as input for another step. This independent execution of steps is advantageous as it eliminates the need to rerun previously executed steps during debugging or software enhancement exercises. Additionally, users have the flexibility to choose specific steps to execute, allowing them to run just individual steps, such as the surface area time series calculation instead of a complete RAT run. The list of steps is shown in Table 2.1. The workflow diagram in Figure 2.4 summarizes the comprehensive process employed by RAT 3.0, executing the 14 key steps to generate essential reservoir data, including inflow, outflow, storage change, and evaporation.

In Step 1 of RAT 3.0, global meteorological data is downloaded, which includes precipitation, minimum and maximum temperature, and wind speed, for the user-provided duration. The [IMERG Late product](#) (Huffman et al., 2014) is used to retrieve daily precipitation, while temperature and wind speed data are sourced from NOAA NCEP/Climate Prediction Center (Kalnay et al., 1996). The data is then scaled, aligned, and clipped to the region of interest. In Step 2, all the

meteorological data is combined into a single NetCDF file in the format required by MetSim (Bennett et al., 2020) for input. The spatial resolution of the data remains fixed at 0.0625° for the entirety of the RAT run. Additionally, Step 3 generates region-specific parameter files for MetSim if not supplied by the user.

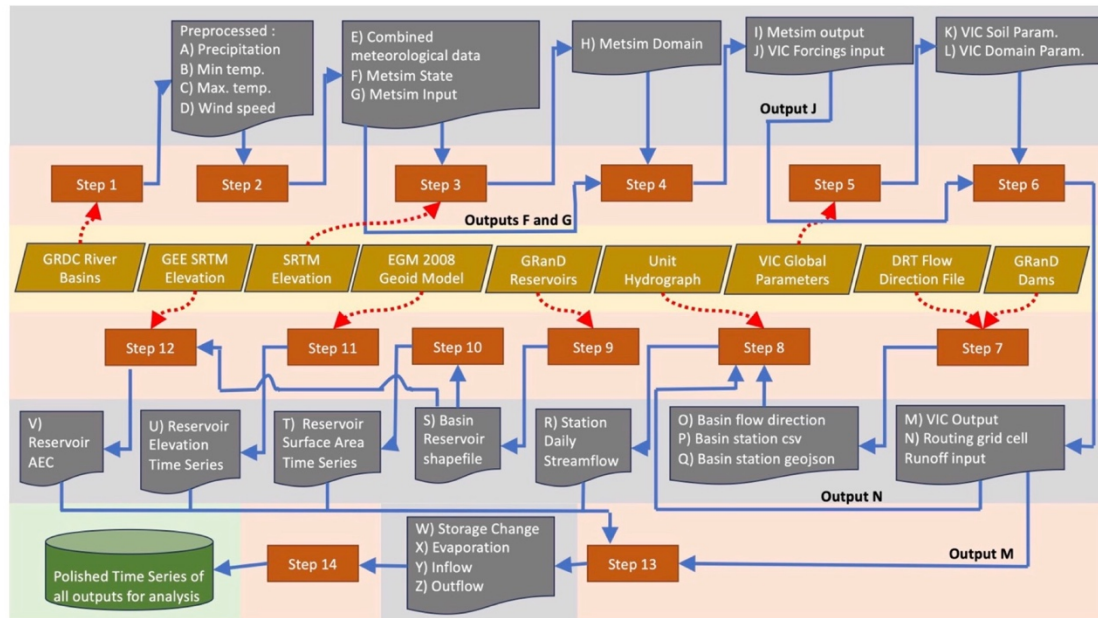


Figure 2.4 Workflow of RAT 3.0 with all the different steps listed in Table 2.1. The yellow layer shows the user inputs, the orange layer shows the flow of different steps or processes, and the grey and green layers show the intermediate and final outputs produced by RAT 3.0, respectively.

After the parameter and input files are prepared for MetSim, Step 4 initiates the MetSim run to produce forcings that are reformatted for input into VIC. If the user has provided parameter files that extend beyond the basin's spatial extent, Step 5 creates VIC's parameter files. Next, in Step 6, VIC generates gridded runoff from the meteorological forcings, which is converted to the format required by the routing model. RAT 3.0 employs the same routing model as RAT 2.0. To prepare for Step 8, parameter files for the routing model are created in Step 7, including the basin's flow

direction file and station file, if necessary. Step 8 involves executing the routing model to generate daily, monthly, and yearly streamflow files for each reservoir.

Step 9 of RAT 3.0 involves the creation of a shapefile for the basin's reservoir polygons using a global reservoir shapefile, if available. In Step 10, the TMS-OS algorithm (Das et al., 2022), and Google Earth Engine (GEE) Python API (Gorelick et al., 2017) are used to produce a surface area time series for each reservoir by efficiently using cloud computing. Step 11 extracts the water level time series for any reservoir that lies on the Jason-3 altimeter track. In Step 12, the area-elevation curve for each reservoir is generated using a digital elevation model, unless provided by the user. Step 13 first calculates the daily inflow for each reservoir using the streamflow files created in Step 8 by the routing model. The storage change time series for each reservoir is then estimated using its surface area/water level time series and area-elevation curve, implementing the trapezoidal rule. The Penman equation of Penman (1948) is then used to estimate the water loss from a reservoir in terms of evaporation. Lastly, Step 13 implements the mass-balance approach to estimate outflow from the reservoirs. Finally, all outputs of the RAT 3.0 are prepared as separate time series CSV files for each reservoir in Step 14.

Table 2.1 List of step numbers and their functions executed by RAT 3.0

Step Number	Step Name
1	Downloading and Pre-processing of meteorological data
2	Pre-processing of data and preparation of MetSim Input
3	Preparation of MetSim Parameter Files
4	Running MetSim & preparation of VIC input
5	Preparation of VIC Parameter Files
6	Running of VIC and preparation of Routing input
7	Preparation of Routing Parameter Files
8	Running Routing
9	Preparation of parameter files for Surface Area Calculation
10	TMS-OS Surface Area Calculation from GEE
11	Elevation extraction from Altimeter
12	Generating Area Elevation Curves for reservoirs
13	Calculation of Outflow, Evaporation, Storage change and Inflow

2.4. Advancements in RAT 3.0

RAT 3.0 introduces several improvements in terms of scalability, robustness, efficiency, ease of use while retaining the power for the user to customize, and improve specific processes in the spirit of open-source software development (Figure 2.5). These advancements are in line with the software design vision to increase the applicability of RAT to diverse fields allied to managed water such as food, energy, fisheries, bio-diversity, drought, recreation etc. Table 2.2 outlines the enhancements introduced in RAT 3.0 as compared to RAT 2.0. One of the most notable improvements in RAT 3.0 is its ability to offer users a global database that can serve as a default configuration. This global database contains input files for VIC global parameters, river basin shapefiles, flow direction and dam geolocation (from GranD) which consequently makes it easier for the first-time user to set up RAT 3.0 at a basin of their choice without requiring much customization.

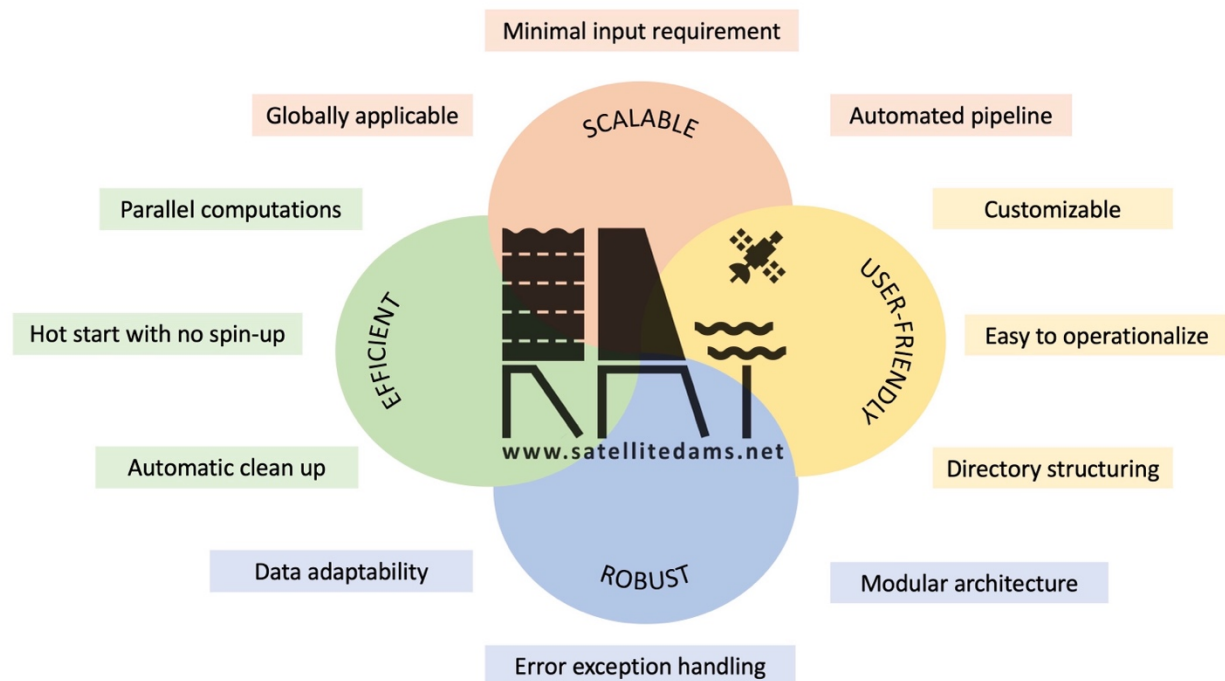


Figure 2.5 Major software design advancements in RAT 3.0.

Table 2.2 Comparison of enhancements in RAT 3.0 as compared to RAT 2.0 in terms of scalability, robustness, user-friendliness and efficiency.

Aspect		RAT 2.0	RAT 3.0
SCALABLE	a)	Limited to Mekong River basin and its dams	Generalized for any reservoir worldwide
	b)	High number of manual input requirements	Automatic input generation reduces number of inputs required from user
	c)	Manual work required to use assets in Google Earth Engine and create inputs	Does not use Google Earth Engine assets; automatic creation of inputs at the time of execution
ROBUST	a)	Does not handle missing meteorological data	Improved handling of missing data with automatic interpolation
	b)	Limited error handling; Difficult to debug with one log file	Enhanced error and exception handling; Easy to debug with 2 log files
	c)	Failure in one component disrupts entire execution	Modular architecture allows independent execution
USER-FRIENDLY	a)	Disorganized output files	Intuitive directory structure for organized outputs
	b)	All inputs were not provided through a configuration file	Single configuration file handles all inputs
	c)	Lack of operationalization feature	Built-in feature for operationalization that works with cron job

EFFICIENCY	a)	No hot-start feature, less efficient use of resources	Hot-start feature for efficient resumption of execution
	b)	Limited use of parallel processing within RAT Framework	Parallelization with Dask library for resource efficiency in RAT Framework
	c)	Accumulation of output files, inefficient memory use	User-selectable automatic deletion of intermediate output files

Also, with the introduction of RAT 3.0, we adopt the semantic versioning system (Preston-Werner, 2023) to define the names of future releases. In this system, version numbers adhere to the format "MAJOR.MINOR.PATCH". A MAJOR version is incremented when changes are made that are not backward compatible, a MINOR version is incremented when new features and functionality are added in a backward-compatible manner, and a PATCH version is incremented for backward-compatible bug fixes. This approach ensures clarity and consistency in communicating the nature of each release.

2.4.1. Scalability

RAT 3.0 operates at the river basin level and can be set up for any river basin worldwide. Users have the flexibility to either select a basin from the global database, allowing RAT 3.0 to automatically set up for the reservoirs within that basin. Alternately, users can provide specific basin geometry and reservoir information for RAT to work with. Moreover, for large-scale analysis, users can select multiple basins simultaneously by utilizing a single configuration file in RAT 3.0. The software also simplifies the creation of region-specific parameter files through automation. The streamlined and automated pipeline of RAT 3.0 allows for global-scale usage, eliminating the need for user dependencies during the process. Notably, RAT 3.0 utilizes a service account to access GEE Python API and converts reservoir geometries into earth-engine objects in real-time. This advancement eliminates the requirement of pre-loading reservoir shapefiles as assets into the user's earth-engine account. This characteristic, in conjunction with RAT 3.0's

software architecture featuring modular components and independent stepwise execution, enhances scalability and user-friendliness.

2.4.2. Scalability

RAT 3.0 conducts thorough validation of user input, which is provided via a configuration file, ensuring crucial checks such as the chronological correctness of start and end dates. The software adopts significant improvements in error handling, implementing a two-level log file system. The first log file (level 1) corresponds to the user's RAT execution, providing concise information on the successful execution of each step for each basin, along with any associated errors. The second log file (level 2) corresponds to a basin for which RAT 3.0 has been executed and offers a comprehensive description of the computations and processes undertaken by RAT for that basin. The level-1 log file also provides the authentication status of the earth-engine service account provided by the user.

In managing missing meteorological data within the designated execution period, the resilience of RAT 3.0 should be noted. The version 3.0 software proactively handles potential issues of file corruption resulting from internet connectivity problems during satellite data file downloads. It triggers an automatic re-download process to ensure data integrity. Users also have the flexibility to provide a climatological dataset specific to the basin, empowering RAT 3.0 to identify unphysical precipitation values that are sometimes produced by satellite data algorithms and substitute them with more realistic alternatives.

To guarantee execution stability, RAT 3.0 integrates robust exception-handling mechanisms that prevent the failure of one step from obstructing the progress of subsequent steps. While the level-1 log file records any encountered errors, it may not provide in-depth insights into the underlying cause. Therefore, users are advised to seek support through the RAT discussion forum at <https://github.com/UW-SASWE/RAT/discussions>, where the engaged user and developer community can assist in diagnosing and resolving specific errors. Additionally, RAT 3.0 verifies

the availability of at least one satellite imagery for each reservoir within the desired execution period before initiating computations in GEE, effectively avoiding potential errors thrown by its Python API.

2.4.3. Efficiency

RAT 3.0 improves computational performance and memory usage. To optimize resource utilization, RAT 3.0 leverages the dask Python library (Rocklin, 2015), enabling parallelization of meteorological data downloads and routing model execution for multiple reservoirs. Additionally, it incorporates a smart mechanism to avoid redundant operations by skipping the downloading and processing of files as well as the creation of parameter files that already exist from previous RAT runs. The configuration file of RAT 3.0 has been expanded to include new sections that correspond to the various steps outlined in the 'Framework of RAT 3.0' subsection. This enhancement allows users to selectively choose a subset of these 14 steps, enabling them to reduce the execution time of RAT based on their specific output requirements or to resume the process from a previous checkpoint.

RAT 3.0 offers automatic handling of the spin-up time required by the MetSim and VIC model, while still allowing users to utilize VIC's 'hot start' feature. In the hot start feature, VIC hydrologic model bypasses the spin-up period and initializes the soil parameters using an existing parameter file, which, in the case of RAT 3.0, represents the soil state conditions at the end of the duration of the last RAT execution. This time-saving capability allows users to seamlessly resume the RAT execution from the point where it last ended, unlike RAT 2.0, which required starting from the beginning to ensure an adequate spin-up period for VIC. This hot start feature brings down the computational burden of any operational cron job involving RAT 3.0. It is worth noting that employing VIC's 'hot start' feature necessitates a spin-up time for the routing model, which varies based on the basin size and the duration required for water to travel from upstream to downstream locations within the basin. RAT 3.0 effectively accounts for this spin-up time to ensure precise and accurate results.

Efficiency in memory usage has been achieved through the elimination of the need to save parameter files for each RAT execution. Moreover, users are offered the convenience of automatically deleting intermediate data while retaining only the final outputs. By default, RAT 3.0 merges newly generated output data with the previously stored results based on the date. However, users have the flexibility to execute RAT 3.0 by replacing the previous outputs, enabling a fresh start when desired.

2.4.4. Ease of Use

RAT 3.0 improves user-friendliness, particularly in the realm of data management. A major improvement is the separation of the data directory from the source code directory. Users are no longer required to keep the data directory in the same location as the source code. This separation proves advantageous when users need to store the data directory on a different disk to overcome memory limitations. Furthermore, RAT 3.0 recognizes the extensive generation of intermediate outputs and parameter files before obtaining the final outputs. To streamline file organization and ease navigation, the data directory has undergone restructuring and re-organization. This allows users to effortlessly locate files associated with specific intermediate processes within RAT 3.0, such as MetSim, VIC, and GEE.

This version of RAT also introduces a convenient built-in feature for operationalizing RAT 3.0, allowing users to specify the desired latency. While the typical latency of meteorological data ranges from 1-2 days, it is advised to set a latency of 3 days when operationalizing RAT 3.0. This ensures that RAT 3.0 obtains all the necessary input data from various satellite data servers and executes smoothly, without encountering any errors. By setting a latency of 3 days, RAT 3.0 will initiate execution from the end of the previous RAT 3.0 run and cover the duration up to three days prior to the current day. This approach guarantees that RAT 3.0 has access to the most up-to-date and reliable input data, providing users with comprehensive results.

The introduction of the global database simplifies the input requirements for utilizing and operationalizing RAT 3.0 for first-time users. The expanded functionality of executing RAT 3.0 for multiple basins or selectively choosing specific tasks (steps) enhances the versatility of RAT. In RAT 3.0, users only need to provide a single configuration file and a secrets file to customize their preferences and provide the necessary credentials. To enhance user visibility and troubleshooting capabilities, RAT 3.0 incorporates two-level logging, enabling users to track the progress of each RAT execution and promptly identify and address any encountered errors or warnings. These combined features significantly reduce the barrier of usage for first-time users, making RAT more accessible to the broader water community.

For additional support and for downloading the RAT 3.0 software, a comprehensive user guide is available on the RAT Global web app, described in the following section. A dedicated discussion forum (see section 3.2) has been established to foster collaboration among RAT users, facilitating the open exchange of experiences, challenges, and specific use cases.

2.4.5. Global Database

While the inclusion of the global database may not be considered a technical advancement specific to RAT 3.0, its presence has brought about a transformative shift in the development of RAT 3.0. Without the global database, the significance of other enhancements in RAT 3.0 would have been diminished. Leveraging various global datasets outlined in Table 2.3, RAT 3.0 now possesses default inputs that enable the execution of RAT 3.0 for any river basin worldwide for the first-time user. This approach allows the user to focus more on improving the skill of RAT iteratively once the initial version is quickly set up and made functional.

The GRDC river basin shapefile [row 1 of Table 2.3] is utilized to generate a grid of the river basin for calculating inflow using VIC and routing models. In addition, the boundary polygon from this shapefile is also employed to select only those reservoirs and dams from the GRand dam database of Lehner et al. (2011) [rows 2 and 3 of Table 2.3] that lie within the river basin. RAT is

then executed for only these dams and calculates inflow, surface area change, evaporation, and outflow. The routing model relies on the flow direction file [row 4 of Table 2.3] to calculate inflow based on gridded runoff data obtained from VIC.

The DEM elevation raster from the Shuttle Radar Topography Mission (SRTM) [row 5 of Table 2.3] is used by RAT to create a domain parameter file required for the execution of MetSim. VIC Soil and Domain Parameter raster files [rows 6 and 7 of Table 2.3] offer global-scale and high-resolution information, respectively, enabling the creation of input parameter files required by VIC. Please note that the VIC Global parameters are uncalibrated. Therefore, users are required to calibrate intricate yet challenging-to-measure parameters, including soil depth and the variable infiltration capacity parameter. Achieving an accurate match between simulated and observed inflow requires careful calibration efforts. For a comprehensive understanding of the calibration process and additional details, we recommend referring to the Usage Notes provided by Schaperow et al. (2021).

Table 2.3 Different datasets along with their description and source, that are included in the global database and are used as default inputs by RAT 3.0 if downloaded by the user.

S. No.	Dataset Name	Brief Description	Additional Information	Reference
1	GRDC Major River Basins	Shapefile of all the major river basins' polygons in the world.	Version - 2 nd Revised Edition, 2020; Src- The Global Runoff Data Centre	GRDC, 2020
2	GRanD Dams	Shapefile of all the major dams' locations in the world.	Version - 1.3 ; Src - https://www.globaldamwatch.org	Lehner et al., 2011

3	GRanD Reservoirs	Shapefile of all the reservoirs' polygons associated with dams in [2].	Version - 1.3 ; Src - https://www.globaldamwatch.org	Lehner et al., 2011
4	DRT Flow Direction	Global raster file providing the flow directions in WGS84 projection.	Resolution - 1/16°; Src- Numerical Terradynamic Simulation Group , University of Montana	Wu et al., 2011, 2012
5	SRTM_30 Elevation	Global elevation raster file providing elevation in meters.	Resolution – 30 arc seconds ; Src - Scripps Institution Of Oceanography, University of California San Diego	Becker et al., 2009
6	VIC Soil Parameters	Global VIC soil parameter dataset containing separate raster files for each continent in WGS84 projection.	Resolution - 1/16°; Spatial coverage from 60°S to 85°N; Version-1.6d ;Src- DOI 10.5281/zenodo.3475601	Schaperow et al., 2021
7	VIC Domain Parameters	Global VIC domain parameter dataset containing separate raster files for each continent in WGS84 projection.	Resolution - 1/16°; Spatial coverage from 60°S to 85°N; Version-1.6d ;Src- DOI 10.5281/zenodo.3475601	Schaperow et al., 2021
8	EGM2008	Geoid model that provides mean sea level in meters everywhere on Earth.	Resolution – 5 arc minutes; Src- National Geospatial-Intelligence Agency (NGA)	Pavlis et al., 2012

Lastly, the EGM2008 geoid model [row 8 of Table 2.3] is used to extract reservoir levels from altimetry data. It is important to note that while these datasets are provided as default inputs for RAT execution, users have the flexibility to override these options according to their preferences and select dam locations that are not in the GranD database. Additionally, if no AEC (area

elevation curve) file is provided for a reservoir, the SRTM 30 m digital elevation model available in GEE is used to automatically estimate the AEC for the reservoirs in question (Farr et al., 2007).

2.5. RAT – Global Web App: The Confluence of Visualization, Training and Access to RAT 3.0 Software

An interactive web application for RAT 3.0 has been developed and can now be accessed at www.satellitedams.net. This platform serves as an informational hub for RAT and provides users with an interactive map to visualize and analyse data from numerous dams worldwide (Figure 2.6). In addition, this global web app offers a comprehensive 'HELP' section where users can access three types of educational and training resources. These are: 1) accessing the source codes from the RAT 3.0 GitHub page; 2) detailed software documentation hosted on ratdocs.io and 3) comprehensive tutorial detailing how to execute each of the 14 key steps for successful execution of RAT 3.0. Those interested in deepening their understanding of the tool can explore the 'PUBLICATIONS' section to access relevant literature and enhance their knowledge.

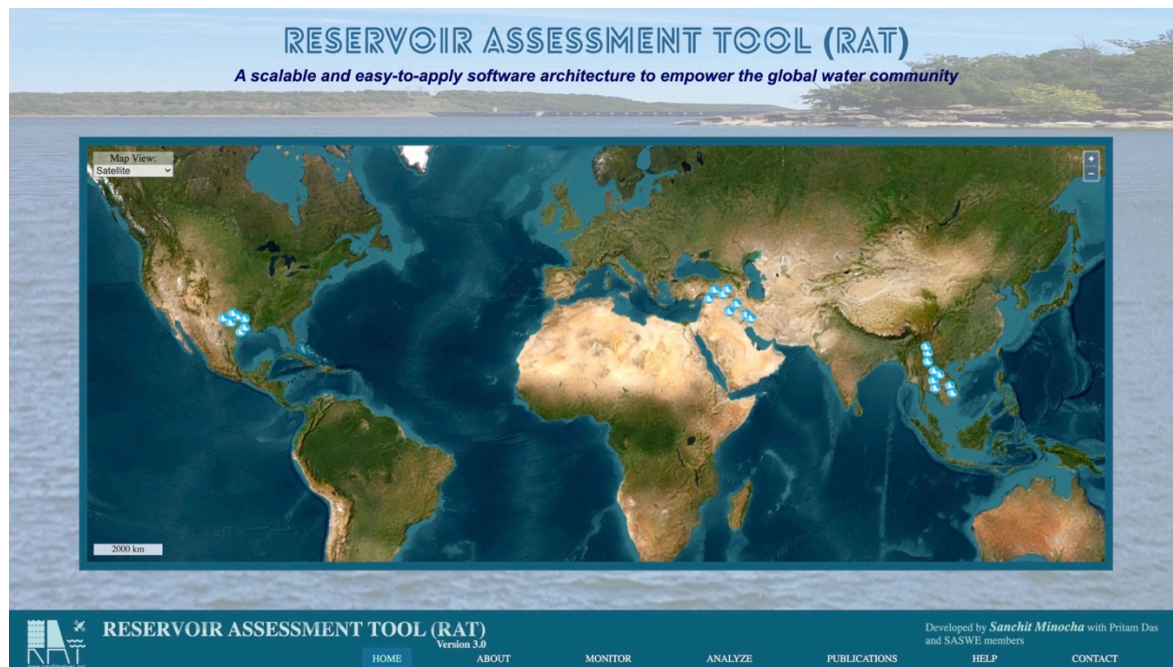


Figure 2.6 Homepage of the front end of the global RAT 3.0's online set up at www.satellitedams.net On the HELP menu, the RAT 3.0 software can be downloaded as well as other resources such as training and education can be found.

The web application has been carefully developed to cater to a wide range of users, including stakeholders, government officials, and the general public. The key idea was to make it easy for users to access and visualize the dynamic outputs on reservoir state that are routinely generated by University of Washington developers to develop a first-cut understanding. Currently, the tool offers data for reservoirs located in the Texas-Gulf, Mesopotamia, and Southeast Asian River basins, with plans to include information on 1600 major dams worldwide that were originally monitored in RAT 1.0 in the near future. Once the tool becomes operational for most of the world's major reservoirs, users will have access to data (with a 3-day latency) on the dynamic state reservoirs (hindcast and nowcast). We firmly believe that every individual user or entity should have equal access to such information of our managed water resources. By making this data publicly available on the global web app, the developers have contributed their part to mitigating the lack of access to water information in transboundary and ungauged river basins.

We have implemented an advanced visualizer feature (Figure 2.7) to expand the capabilities of the web application and meet the diverse requirements of different entities and stakeholders. With this feature, users can extract meaningful information without the hassle of downloading the data, allowing for a more streamlined and efficient analysis process.

The advanced visualizer component allows users to conduct in-depth analyses using the reservoir data by plotting multiple axes on a single interactive graph, such as discharge, surface area, and storage change (Figure 2.8). This functionality extends to any two reservoirs globally, providing the flexibility to perform comparative analyses (see Figure 2.9 and Figure 2.10). For instance, users can compare the outflow of an upstream dam with the inflow of a downstream dam, shedding light on the dynamics between the two. Another scenario may involve plotting the surface area of a reservoir alongside its inflow, allowing users to gain a comprehensive understanding of the relationship between these reservoir state variables (Figures 2.6-2.10).



Figure 2.7 Advanced visualizer feature to meet the diverse requirements of different entities and stakeholders.

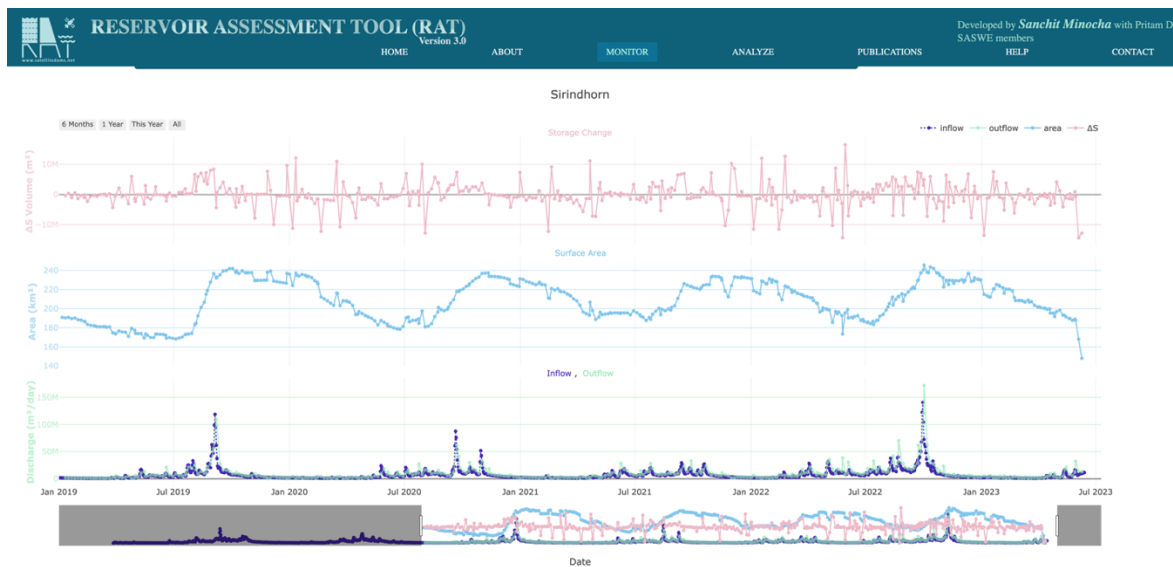


Figure 2.8 Reservoir data for one of the reservoirs 'Sirindhorn' (shown in Figure 6 (e)) in the Mekong River basin produced by RAT 3.0.

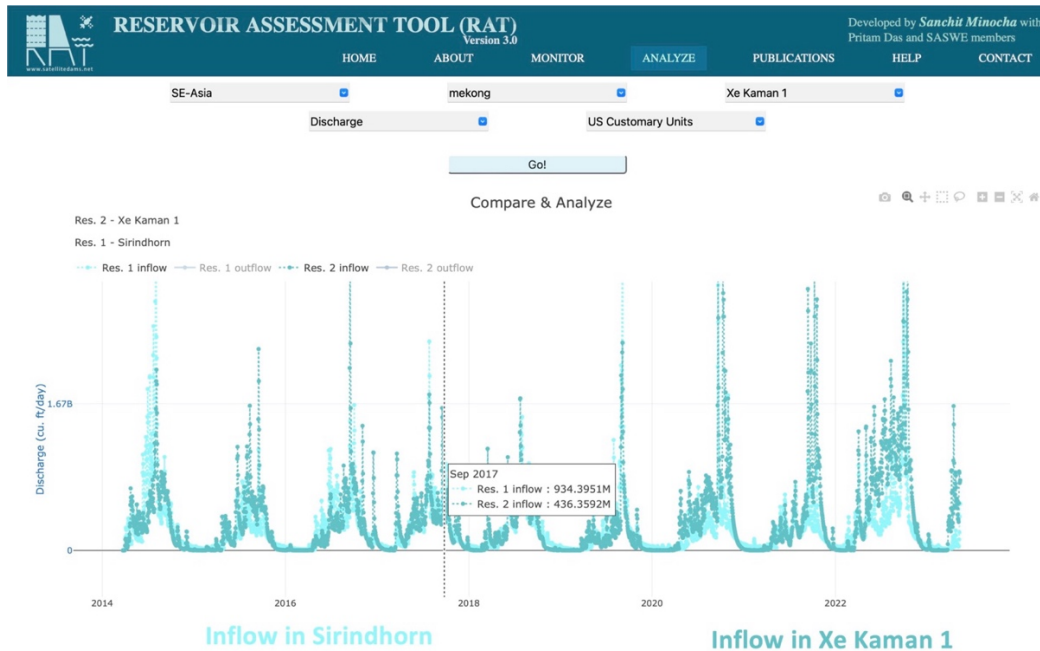


Figure 2.9 Inflow for ‘Sirindhorn’ in the Mekong River basin is compared to another nearby reservoir ‘Xe Kaman 1’ (shown in Figure 6 (e)) using the advanced visualizer feature.

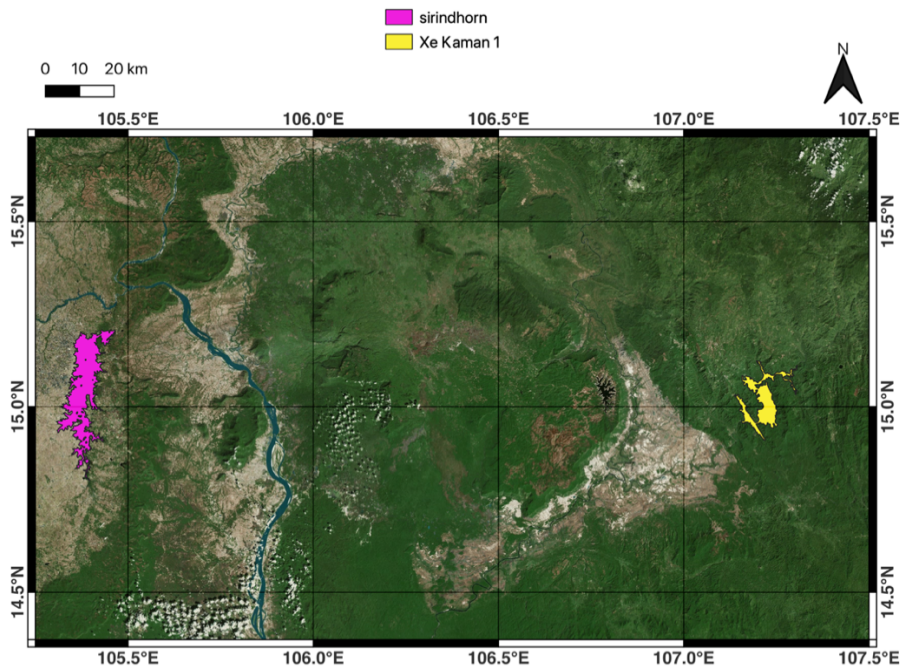


Figure 2.10 Reservoirs Sirindhorn and Xe Kaman 1 shown on the map for comparative analyses of RAT outputs on the global web app of RAT at www.satellitedams.net.

2.6. Applications: Leveraging RAT 3.0 in Practical Scenarios

The versatile capabilities of RAT 3.0 extend across a range of critical hydrological and environmental applications, offering a valuable modelling platform for researchers and practitioners alike. The below mentioned use cases showcase the efficacy of RAT 3.0 in addressing complex challenges in diverse geographical settings. From tracking extreme flooding in the mountainous terrains of Kerala, India, to the development of algorithms like ResORR for estimating regulated inflow demonstrates its prowess in hydrological modeling and analysis. This section provides a glimpse into the manifold applications of RAT 3.0, emphasizing its significance in advancing our understanding of impact of reservoir dynamics in different regions worldwide.

1. Studying flood tracking in mountainous regions characterized by high precipitation and steep terrain, with a specific focus on the 2018 floods in Kerala, India using RAT 3.0 (Suresh et al., 2023). In this study, RAT 3.0 was able to clearly track extreme flooding in a highly mountainous and high precipitating region with perennial cloud cover and hydropower dams that compete with flood control. RAT3.0 was able to demonstrate that using the framework the timing of the peak flooding, the onset of sudden flooding and the time to recede can all be captured by using only satellite data and RAT 3.0 (Figure 2.11 and Figure 2.12).
2. Use of RAT 3.0 to assess the impact of the Belo Monte Dam on the Xingu River in the Amazon (Hossain et al., 2023a). In this study, RAT 3.0 was able to pick up the historical hydrologic response to precipitation of the region during the post-dam period (after the Belo Monte dam was constructed).
3. Use of RAT 3.0 to develop algorithm (called ResORR) to estimate regulated inflow using VIC's natural inflow (which assumes the absence of upstream dams) with study site as Tennessee River basin. In this study RAT 3.0 combined with modeling of regulation of flow by upstream reservoir storage was found able to consistently predict well the downstream inflow to a series of reservoirs (Figure 2.13 and Figure 2.14).

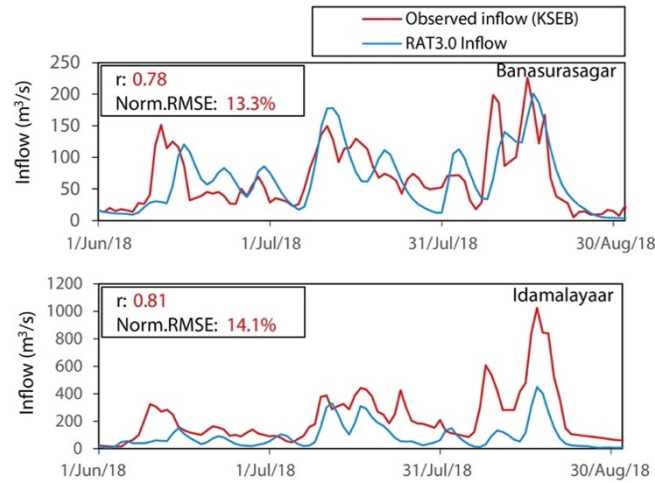


Figure 2.11 RAT hydrographs comparing observed inflow at Banasurasagar and Idamalayaar dam (red) against hydrologic model inflow by RAT using VIC (blue) during the 2018 Kerala floods. After Suresh et al. (2023). See Figure 2.12 for a map of Banasurasagar and Idamalayaar dam in Kerala.

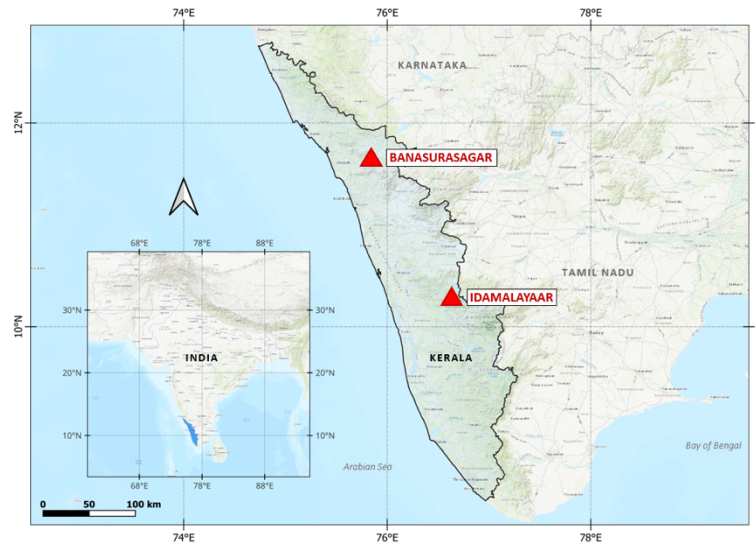


Figure 2.12 Map of Kerala with the location of the Banasurasagar and Idamalayaar dam. After Suresh et al. (2023).

4. Valuable insights provided by RAT into the effects of dams in the transboundary river basin of Mesopotamia (Hossain et al., 2023a). In this study, RAT was developed, set up and operationalized over the Tigris Euphrates River basins exclusively to demonstrate to

stakeholders such as Iraqi Ministry of Water Resources what is possible for transboundary reservoir monitoring using satellite data alone. Readers can see the operational system running at <https://depts.washington.edu/saswe/rat>. The scientific potential of this RAT rendition is that it brought various communities together to discuss how the Mesopotamian rivers could be restored and how the downstream marshland could be revised using techniques such as RAT when there is no in-situ data or publicly available modeling tools.

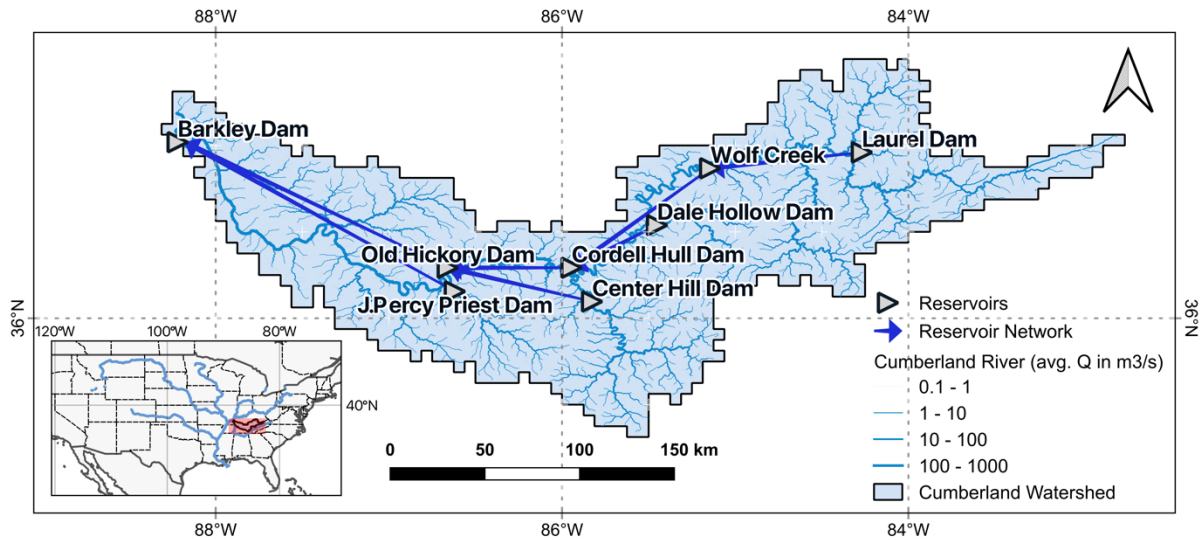


Figure 2.13 Map of the Cumberland basin where the ResORR algorithm to model regulated inflow for RAT was developed and test. The map shows locations of the reservoirs, the reservoir network, and the location of the Cumberland basin in the US.

5. Analyzing the role of reservoirs on downstream river temperature using RAT 3.0 for Columbia River basin. In this study, RAT generated reservoir storage was able to improve the remote sensing-based surface water temperature estimation in the 50 km downstream reach of the Columbia River dams. With RAT derived storage change, there was about 50% reduction in RMSE of temperature prediction (Figure 2.15).

2.7. Discussion and Conclusion

In a world where dams continue to be constructed or maintained at a rate faster than they are dismantled, it is important to acknowledge that dams are here to stay in the foreseeable future with

their inherent advantages and disadvantages. Our focus here is on mitigating the negative impacts associated with these structures by levelling the playing field of access to information on the dynamic state of the world's reservoirs. Timely understanding of how dams and reservoirs affect natural river flow and other important water parameters is crucial in achieving this goal. Real-time monitoring of reservoirs is also essential for effectively addressing immediate threats such as floods and droughts. RAT 3.0 makes such monitoring possible with satellite remote sensing missions that have emerged as an indispensable vantage for studying reservoir operations and their impact on surrounding areas.

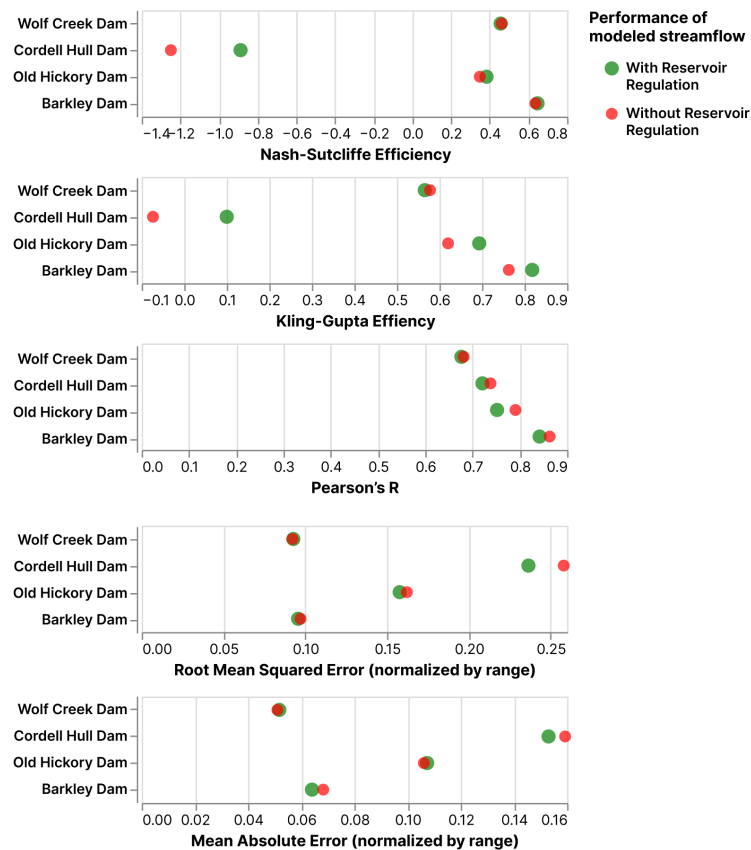


Figure 2.14 Performance of RAT-generated regulated inflow using ResORR compared to the unregulated inflow modeled using VIC in the regulated Cumberland River basin in terms of performance metrics. The chart shows that it is clearly improving simulations when compared to the baseline (unregulated inflow) for most dams.

In this paper, we have described the redesigned software architecture of RAT 3.0 that can be executed on any Unix operating system and even on supercomputers by making use of parallelization. The operating system constraint arises from the VIC hydrological model's exclusive compatibility with Unix OS. Consequently, a standard laptop with 8 GB RAM, 4 cores, and a 512 GB hard disk is sufficient for running RAT 3.0, with the computational time contingent on the size of the river basin.

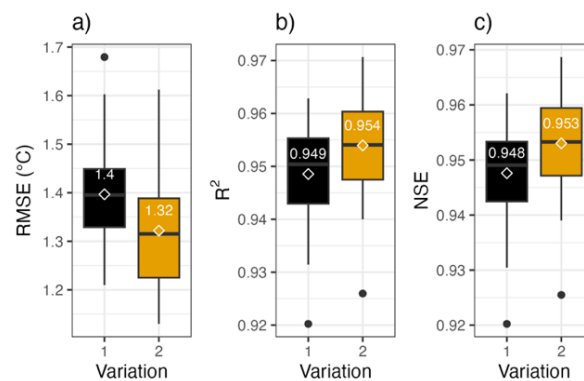


Figure 2.15 The impact of using RAT based reservoir storage change on improving river temperature prediction. Black is without using RAT and yellow is with using RAT storage change at more than 50 river reaches downstream of dams in Columbia river basin.

The modular design of RAT 3.0 with 14 self-contained steps makes it possible for a user to execute RAT only for a desired set of tasks. This enhances the user-friendliness of RAT 3.0 and lowers the barrier of entry for the first-time user. Several improvements, like multiple log files, reduction of input requirements, and provision of customization using a config file, have been done to maximize user-friendliness. Error handling has been improved and RAT 3.0 is now more robust when input data is unstable or missing. RAT 3.0 is computationally more efficient by adopting parallelization during downloading and processing meteorological data and the automatic deletion of intermediate files. Finally, RAT 3.0 has been developed with global scalability in mind so that it can be set up for any reservoir system worldwide. Scalability is the most important consideration for developing and nurturing a self-sustaining community of users who can continuously improve such a software in the spirit of open-source development and open science.

RAT 3.0 simulation can span from a single day to multiple decades and is dictated by the hydrologic model's smallest time step and satellite observation frequency. The Tiered Multi-sensor- Optical/SAR (TMS-OS) algorithm, that calculates reservoir storage change based Sentinel-1 SAR, Sentinel-2, and Landsat satellites, allows RAT 3.0 to operate from 2015 onwards. However, single-sensor functionality can be extended to the early 80s, utilizing Landsat 4 data as has been demonstrated by Biswas and Hossain (2021).

RAT 3.0 has already undergone extensive global testing across various basins by multiple users, as illustrated in Figure 2.16, covering a wide range of use cases. Notably, RAT 3.0 has been instrumental in studying flood tracking in mountainous regions characterized by high precipitation and steep terrain, with a specific focus on the 2018 floods in Kerala, India (Suresh et al., 2023). It has been utilized to assess the impact of the Belo Monte Dam on the Xingu River in the Amazon (Hossain et al., 2023b) and to compute and compare regulated inflow with natural inflow in the absence of upstream dams in the Tennessee River basin. RAT 3.0 has also provided valuable insights into the effects of dams in the transboundary river basin of Mesopotamia (Hossain et al., 2023a). Recently, RAT was upgraded by the Asian Disaster Preparedness Center (ADPC) from version 2.0 to 3.0 for the Mekong River basin with assistance from co-author Pritam Das (see <https://ratmekong-servir.adpc.net/>). This version currently serves as an operational system for the MRC stakeholders. Currently, RAT 3.0 is being employed to analyse the hydro-thermal history of the Columbia River in the Pacific Northwest and upgraded from version 1.0 for the Nile and Indus River basins (Figure 2.16). The fact that RAT 3.0 is applied in various river basins, coupled with the reduced setup time to a week from 3-4 months (for RAT 2.0), highlights the scalability and user-friendly architecture of RAT 3.0.

RAT 3.0 does not represent the final word on satellite-based reservoir monitoring software development. There will undoubtedly be numerous unforeseen software hurdles or bugs that will emerge as the use of RAT 3.0 expands. New satellite missions will emerge, and many current ones may become less relevant, requiring updating of certain components of the software architecture. One such satellite mission is the recently launched Surface Water and Ocean Topography (SWOT)

mission that will produce more accurate reservoir storage level, area and change data. Based on simulation studies reported by Bonnema and Hossain (2019), we believe SWOT will “turbocharge” the accuracy and operational efficiency of RAT 3.0 (see also Hossain et al., 2023a; 2022).

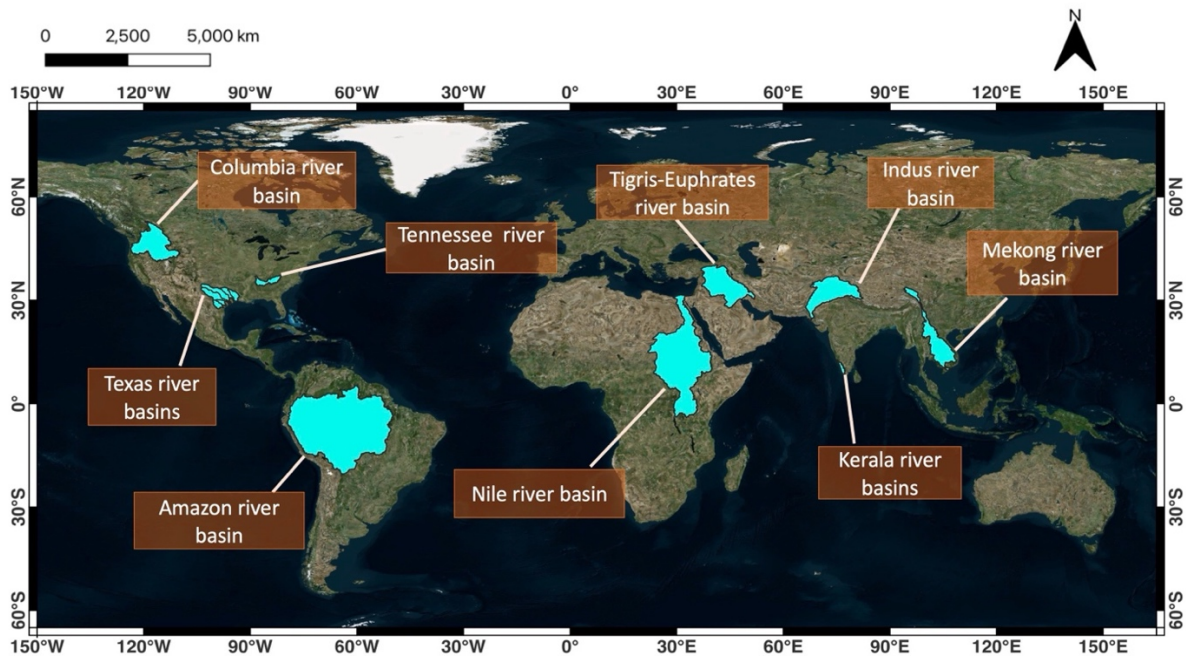


Figure 2.16 River basins where RAT 3.0 has been (or is being) independently installed and tested by users.

The impact of sedimentation on reservoir storage is a critical consideration addressed in RAT 3.0. The framework's modular design allows users to dynamically update the area-elevation relationship, ensuring accurate simulations even in the presence of sedimentation. Localized applications in the Mekong and Cumberland River basins have showcased the framework's adaptability in representing changes in bathymetry due to sedimentation (Das et al., 2022). However, extending this capability globally faces challenges due to the lack of time-varying global digital elevation models (DEM). For pre-2000 reservoirs, such as those covered by the Shuttle Radar Topography Mission (SRTM), representing sedimentation requires additional parameterizations or satellite observations when the reservoir was at lower levels (Bonnema et al., 2017). Future research endeavors with RAT 3.0 will explore potential solutions, involving

sediment trapping concepts and the integration of satellite geodetic observations, to enhance its global scalability in addressing sedimentation challenges.

The calibration and choice of the hydrologic model play a crucial role in RAT's performance, as it relies on the accuracy of unregulated inflow capture, especially at the headwaters. A recent study by co-author Pritam Das highlights the importance of hydrologic model calibration up to the last upstream boundary point where flow remains naturalized. Beyond this point, sensitivity to calibration decreases, emphasizing the significance of assimilating reservoir storage changes to account for regulated flow downstream using an appropriate regulation algorithm. Thus, RAT is purported to be hydrologic model agnostic. In its current architecture RAT 3.0 is not yet streamlined to allow easy swapping of the hydrologic model, select specific satellites and input data streams by the user. All these issues will no doubt be addressed in a future and minor upgrade of RAT 3.0. What is important to note is that with the wholesale overhaul of the RAT software architecture in version 3.0, we now have the necessary design spirit of user-friendliness, scalability, open-access and open-sharing embraced to nurture a self-sustaining community of users who can continuously improve satellite-based reservoir monitoring based on grassroots needs of users.

The current applications of RAT 3.0 mark the advent of a new era, where the combined power of high-performance computing, information technology and satellite earth observations enable us to deepen our understanding of dams and their ecological impacts. RAT 3.0 represents the vanguard of this progress, offered to the global community as the first stride towards advancing reservoir management practices and bringing them up to speed in the 21st century space age. As water demand continues to escalate, RAT 3.0 equips water resource managers and stakeholders with invaluable insights to make informed decisions and optimize the utilization of scarce water resources. With RAT 3.0, it is our hope that the deep-seated disparities among nations pertaining to transboundary rivers can be drastically reduced, contributing to a more harmonious world. We believe the day is not far when the transformative power of the open source and collaborative software development spirit of RAT 3.0 will touch the lives of all, ensuring equal access to information on the reservoir's dynamic state.

Yet the promise of a global monitoring platform is only fully realized when it is accessible enough for any researcher or water manager—regardless of institutional resources—to deploy independently. RAT 3.0's architecture provides the computational and scientific backbone, but accessibility at scale demands a still lower barrier to entry: a properly packaged, version-controlled software library that installs in a single command, self-tests its own correctness, and ships with living documentation. Chapter 3 therefore turns from the framework design to its operationalization, describing how RAT 3.0 was refactored into a Conda-distributed Python package that extends the tool's reach from a small community of technical experts to the broader global water community.

Chapter 3. Reservoir Assessment Tool (RAT): A Python Package for monitoring the dynamic state of reservoirs and analyzing dam operations

Note: This chapter has been published in its current form in *Digital Water*. The only differences are in the numbering of figures, tables, and references to other sections. [Publication: Minocha, S., Das, P. and Hossain, F. (2025). Reservoir assessment tool (RAT): a Python package for monitoring the dynamic state of reservoirs and analyzing dam operations, *Digital Water*, 3(1), pp. 1–30. <https://doi.org/10.1080/28375807.2025.2487762>]

3.1. Abstract

Advancements in satellite remote sensing has enabled the global tracking of reservoir operations, with the Reservoir Assessment Tool (RAT) emerging as a scalable modeling framework that captures the complete dynamic picture of a reservoir consisting of inflow, storage change, evaporation, surface area and outflow. To address the challenges regarding time-consuming installation and the lack of proper forum and documentation to update and test newer versions, we present RAT as a Python library, conveniently packaged with conda, and as a user-friendly command line utility. This simplifies installation, catering to both programming and non-programming users. Test cases and a Continuous Integration/Continuous Development (CI/CD) pipeline ensure robust code integration and community contributions. Thorough documentation is hosted at <http://ratdocs.io>. The transformation of RAT from a modeling framework into a self-reliant package enhances its usability, reliability, and collaborative nature, solidifying its position as a valuable tool at the nexus of remote sensing and hydrologic modeling.

3.2. Introduction

The data related to inland water quantities, regulated by dams with reservoirs, holds profound significance not only for water scientists but also for various fields such as food production, energy generation, and climate modeling (Jackson et al., 2001). The availability of surface water in a region is no longer solely determined by natural factors such as precipitation; human activities. Dam operations now exert significant influence over reservoir levels (Adrian et al., 2009). For ease

of understanding and to maintain simplicity for a broad audience, the terms ‘dam’ and ‘reservoir’ will be used interchangeably, from here onwards, to refer to the artificial lakes created behind the dams. Water managers rely on this data to allocate water for domestic, industrial, and irrigation purposes, informing future plans and policies. Climatologists utilize this information to analyze the impact of dams on the environment and the dynamic climate. Additionally, ecologists find value in this data to comprehend the role of dam operations in relation to fish and wildlife ecosystems (Johnson et al., 2004). Therefore, this data plays a pivotal role in various fields, reflecting its broad-reaching implications beyond the realm of water science.

Traditional methods of monitoring and acquiring data, such as gauges and flow meters, are not only time-consuming but also economically burdensome (Campbell, 2009; Pimenta et al., 2025). Moreover, the collected data is not consistently shared openly. Restrictions to data are often imposed by political hurdles that do not align with the basin-wide need for reservoir management. This disparity in data sharing can lead to downstream nations experiencing the adverse effects of poorly managed dam operations by their upstream counterparts, including droughts, floods, or compromised water quality (Hossain et al., 2023).

In addressing these challenges, satellite remote sensing can be a promising solution for monitoring dynamic reservoir conditions. While many satellite datasets are freely available, some products require a subscription or purchase. Nonetheless, it remains a cost-effective alternative to ground-based traditional monitoring methods, providing real-time global data (Bonnema and Hossain, 2017; Bonnema et al., 2021). Despite these advantages, existing studies and remote-sensing tools often exhibit limitations, such as regional constraints or an inability to capture the complete dynamics of reservoir operations. Though, there are Python packages like PyGEE-SWToolbox (Owusu et al., 2022) and InfeRes (Mahto and Galelli, 2024) that can measure water body surface areas, they often overlook the potential of cloud computing for satellite image processing, do not integrate distributed physical modeling of the landscape, or are unsuitable for automating workflows (Owusu et al., 2022; Cordeiro et al., 2021).

The Reservoir Assessment Tool (RAT) is one such modelling platform that can estimate various parameters like inflow, outflow, storage change, evaporation, and water level/surface area of a reservoir using satellite-based observations (Biswas et al., 2021; Das et al., 2022). To the best of our knowledge, there is no python package or any other remote-sensing based tool that offers such a comprehensive and complete view of dynamic state vector of reservoirs (comprising inflow, outflow, surface area, elevation, and evaporation).

The RAT uses daily meteorological data that includes precipitation, minimum and maximum temperature, and wind speed from different webservers. This data is then fed to a hydrological model, which currently is Variable Infiltration Capacity (VIC) (Hamman et al., 2018), to derive inflow into a reservoir (Figure 3.1 (e) & (f)). The satellite imagery is used to extract the surface area of a reservoir at different dates (Figure 3.1 (b) & (c)). The Penman equation (Penman, 1948) is used to estimate evaporation from a reservoir using surface area and the meteorological data while the difference in the surface area at two different dates is used along with Area Elevation Curve (AEC) to get elevation difference and thus, the storage change (Figure 3.1 (a) & (d)). AEC can be provided by the user for each reservoir or will be generated automatically using the digital elevation model¹ hosted in Google Earth Engine. Once the inflow, evaporation, and storage change are estimated, outflow is calculated using the mass balance approach ($\text{Outflow} = \text{Inflow} - \text{Evaporation} - \text{Storage Change}$), ignoring any soil seepage as illustrated in Figure 3.1 (Minocha et al., 2024).

Recently, the third and latest version of RAT acquired a completely overhauled architecture that makes it applicable worldwide. It has been applied in the diverse regions globally, including Kerala, India (Suresh et al., 2024), Tennessee, USA (Das et al., 2024), the Middle East (Hossain et al., 2023), and the Columbia River, USA (Darkwah et al., 2024), showcasing its versatility across different use cases and geographies. Noteworthy features of this architecture include the scalability, error-handling capabilities, and robustness in dealing with missing meteorological data, a crucial component for running hydrological models. The revamped architecture also

¹ <https://csidotinfo.wordpress.com/data/srtm-90m-digital-elevation-database-v4-1/>

enhances computational efficiency by incorporating parallel processing for the downloading and processing of meteorological data and makes it user-friendly, requiring minimal inputs from a user (Minocha et al., 2024). These attributes position RAT as a tool for enabling breakthroughs across hydrology-related fields.

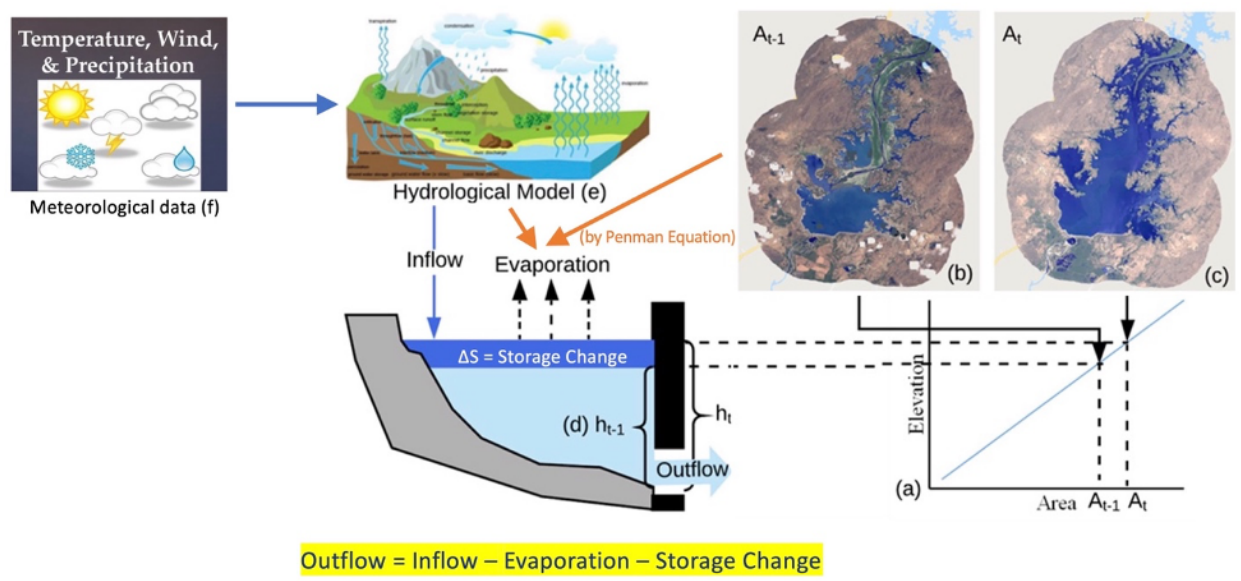


Figure 3.1 Different components of RAT Framework to estimate inflow, evaporation, storage change and outflow for a reservoir (After Minocha et al., 2024).

While the RAT holds the potential to drive advancements in research and enhance water management practices, its widespread adoption may be hindered by the absence of a streamlined channel for setting up the model and its dependencies. Despite the user-friendly architecture of RAT 3.0, the tool might struggle to reach a broader audience within the water community if the installation process proves challenging. Additionally, there is a critical need for a systematic method to test and verify the correct installation of the model. Given RAT's status as an open-source model that encourages contributions from the community, there is a further imperative for automated testing mechanisms to ensure that contributed code functions as intended. To facilitate the seamless utilization, users should have straightforward ways to update and access the latest model versions. Therefore, addressing these installation and testing challenges is essential for

maximizing the impact of RAT and promoting its effective integration into water-related research and management practices.

This paper introduces the RAT as a Python library and presents it as a command line utility, with the goal of enhancing its accessibility to a broader community of tool developers for river studies. Because the RAT harnesses the synergies of remote sensing and hydrologic modeling, we believe it should be presented as a cohesive package. This approach alleviates concerns about the installation of disparate components of the hydrologic model or other dependencies, offering users a seamless experience. To facilitate this, Conda serves as a channel, streamlining the installation process across diverse operating systems. Consequently, a self-installation feature has been integrated into the RAT package, ensuring the download of all the necessary requirements.

The paper delves into the system requirements for the RAT library and explores how the computational efficiency can be heightened by utilizing a greater number of CPU cores. The establishment of the library also facilitates the development of plugins by the growing community, catering to diverse functionalities. It can also benefit the research community by providing time-saving utility functions to analyze the resulting outputs from RAT. A case-study showcasing an application of the library is also included to demonstrate the ability of RAT in tracking reservoir operations.

3.3. Building a Python Library

3.3.1. Dependencies

While RAT's source code is entirely Python-based, its execution requires the installation of a hydrological model and essential Python dependencies. The current RAT architecture uses the VIC hydrological model to compute reservoir inflows. However, VIC relies on MetSim (Bennett et al., 2020) for input forcings to generate surface runoff across a river basin which then requires a routing model (Hamman et al., 2018) to estimate streamflow at the dam location. Though MetSim operates in Python, VIC, coded in C, requires compilation using a C compiler like gcc. The Fortran-based routing model used by RAT requires a compiler such as gfortran. Additionally, creating executables for each of these models involves the use of the make utility to read the makefile. Consequently, a Unix-based operating system is crucial for the entire hydrological model to operate seamlessly.

The multiple language dependencies, spanning Python, C, and Fortran, pose a challenge for users attempting to install them separately, particularly given their OS-dependent nature. To streamline the installation of these diverse language dependencies, many software applications make use of a package manager. Conda, a cross-platform, language-agnostic binary package manager, adeptly handles dependencies across multiple languages. Therefore, RAT has been packaged using Conda and integrated into conda-forge, a community-led organization that hosts Conda packages for a wide array of software applications (conda-forge community, 2015). Beyond addressing dependency issues, Conda also simplifies the process for users to update the software to its latest version.

Table 3.1 List of dependencies of RAT python library.

S. No.	Dependency Name	Functionality
1.	python >=3.6	To execute RAT's source code
2.	make	For reading makefile and creating executable of routing
3.	gfortran	For compiling routing source code
4.	wget	To download meteorological data from different servers
5.	rasterio	To read and write raster data like precipitation from/to raster files
6.	xarray	To manipulate raster data in the form of data structures
7.	rioxarray	To read and write raster data from/to the data structures
8.	earthengine-api	To access Google Earth Engine Python API
9.	pandas	To read, write and manipulate tabular data like inflow timeseries
10.	geopandas	To read and write georeferenced tabular data like shapefiles
11.	numpy	For mathematical operations in the form of arrays
12.	netcdf4	To read and write NetCDF files.
13.	dask	To do parallel computations for routing; download weather data
14.	scipy	Interpolation methods used by TMS-OS (Das et al., 2022)
15.	scikit-learn	Clustering methods used to extract height from altimetry data
16.	ruamel_yaml	To read and write configuration file with comments
17.	yaml	To read and write configuration file
18.	gdown	To download global database from google drive

Table 3.1 lists the dependencies installed when RAT Python library is installed using Conda. While conda effectively handles the installation of the dependencies necessary for setting up the hydrological model (such as the make utility), it doesn't automatically install specific components of the hydrological model that includes VIC, MetSim, and the routing models. Both VIC and MetSim are available as Conda packages, but challenges arise due to compatibility issues stemming from their need for different versions of common libraries. This incompatibility necessitates users to install them in separate environments. Here 'environments' refer to separate setups on a computer where different software tools can run without interfering with each other. These setups allow users to manage dependencies and avoid conflicts between programs, ensuring that each tool operates correctly. Additionally, the routing model, not offered as a Conda package, mandates users to download the source code and manually compile it using the compiler installed by Conda during the RAT installation. Collectively, these factors make it necessary to install all the three models individually and manually. This problem has been addressed in section 3.4.1.

3.3.2. System Requirements

The execution of RAT involves two computationally intensive processes. Firstly, the hydrological model, and secondly, the processing of satellite imagery to derive surface area estimates for a reservoir. For efficient satellite imagery processing, RAT leverages cloud computing through Google Earth Engine (GEE) (Gorelick et al., 2017). As a result, the primary requirements of RAT are driven by the hydrological model. Currently RAT uses the VIC hydrological model for inflow estimation which requires a Unix-based operating system.

Like most other Python libraries, there are no specific minimum specifications for a machine for RAT. A standard laptop equipped with 4 GB RAM, a 512 GB hard disk, and 2 CPU cores is sufficient to run RAT. However, more powerful machines with increased RAM and CPU cores can significantly reduce computational time. Table 3.2 compares the computational time (measured in wall time) on two different machines—a standard laptop (MacBook) and a server machine. Wall time is the actual time elapsed between the start and end of the execution of a computer program. The execution of RAT was conducted for the Hidkal Dam in the Krishna River Basin of India (see Figure 3.2) over a one-year period from January 1, 2019, to December 31,

2019. No spin-up for the hydrological model was required as initial state files were used. In the context of hydrological modeling, 'spin-up' refers to the process of running the model for a period of time before the actual simulation starts, to ensure that the model reaches a stable state.

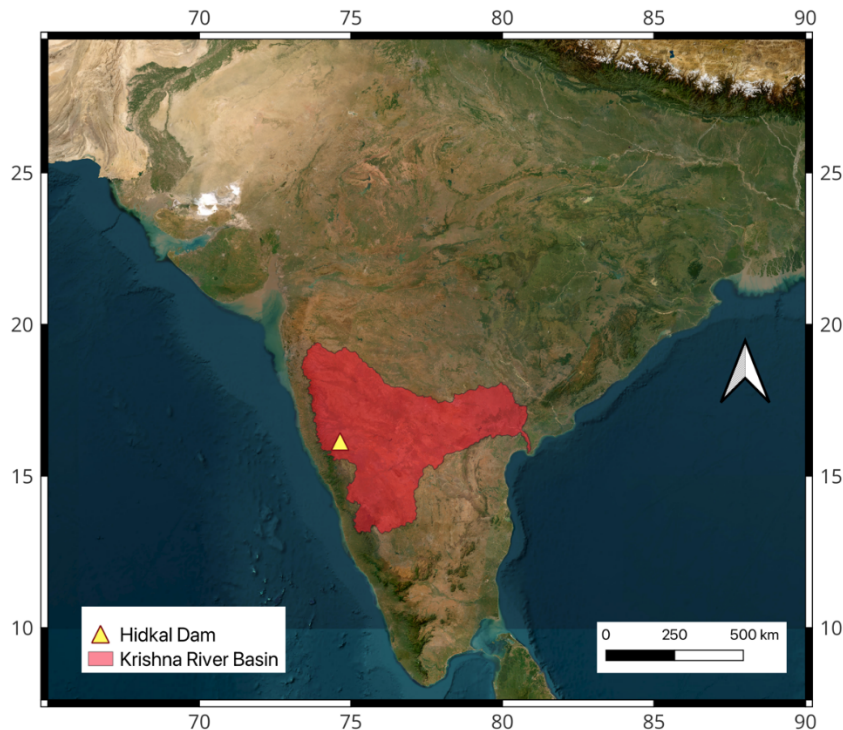


Figure 3.2 Map of the Krishna River basin in India, showing location of the Hidkal dam/reservoir.

It should be noted that the wall time for surface area estimation is independent of the machine specifications as it is dependent on the cloud machine provided by GEE. Also, with a greater number of cores the total run time reduces significantly as RAT makes use of parallel computations. Another noteworthy observation is the substantial increase in MetSim's wall-time on the server machine when utilizing a single core compared to a single core on a less powerful machine. One of the potential reasons for it could be that the computational efficiency of MetSim may not be fully optimized for the enhanced processing capacity of the stronger machine. This behavior indicates the need for a deeper investigation into MetSim's compatibility with varying hardware configurations, shedding light on potential optimizations and areas for improvement.

Table 3.2 Computational wall time comparison of RAT for different machines using different number of CPU cores.

System Specifications	Macbook Laptop: 2.3 GHz Dual-Core Intel Core i5 CPU; 16 GB RAM; Mac OS		Server Machine: 3 GHz Intel(R) Xeon(R) Gold 5317 CPU with 48 cores; 256 GB RAM; Linux OS	
Number of cores used	1	4	1	48
Run Time to download meteorological data	240.17 minutes	170.95 minutes	22.02 minutes	3.2 minutes
Run Time for MetSim	17.95 minutes	15.08 minutes	68.32 minutes	8 minutes
Run Time for VIC	15.63 minutes	15.05 minutes	9.97 minutes	1.72 minutes
Run Time for Routing	3 seconds	3 seconds	2 seconds	1 second
Run Time for Surface Area Estimate	7.93 minutes	8.32 minutes	9.68 minutes	10.52 minutes
Total Run Time	280.48 minutes	211.82 minutes	110.8 minutes	24.4 minutes

3.4. Enhancements Incorporated in the Python Library

To improve accessibility and expand the user base, a command-line interface (CLI) has been integrated into RAT while building the package using Conda. This CLI not only introduces additional functionalities for enhanced user convenience but also promotes inclusivity by catering to individuals with diverse technical backgrounds. Besides the CLI, several utility functions have been added as a part of the library that facilitate users and developers while using RAT. This section describes the various functionalities added to the RAT package.

3.4.1. Initialization

As discussed in section 3.3.1, RAT requires separate and independent downloading and installation/compiling of MetSim, VIC and the routing model. To simplify this process, the CLI command 'rat init' streamlines RAT's initialization. It accomplishes this by automatically downloading and installing the required Python environments for MetSim and VIC, as well as fetching and compiling the routing scripts. Moreover, it acquires several default parameter files

necessary for VIC, MetSim, routing, or RAT with the option to modify these files as necessary during calibration and validation. This command also offers users the option to download a global database, encompassing multiple global datasets, which can serve as the default values for a newly set-up RAT instance (Minocha et al., 2024). The command requires a path to the directory where all the models will be installed and data will be downloaded, referred to as the project directory in the context of RAT. Notably, the initialization of RAT is a one-time requirement following the installation of the RAT Conda package.

3.4.2. Testing

Once RAT has been installed and initialized, users can test the functioning of RAT by using 'rat test' command in CLI. It requires users to provide a 'secret file,' which is an '.ini' file containing credentials for using Google Earth Engine and for downloading IMERG precipitation data (Huffman et al., 2014) along with Jason-3 altimetry data. Other than the secret file a user needs to specify the path of the project directory and the name of the test river basin. Currently, users can choose between two test basins: Nueces in Texas (Figure 3.3) or Gunnison in Colorado, USA, (Figure 3.4) to test if RAT has been installed and initialized correctly. This command downloads a test dataset with parameter files for the chosen test river basin and expected results. It runs RAT for that test basin and compares the outputs to expected results across six test cases: inflow, outflow, surface area, storage change, evaporation, and area elevation curve. It also validates the user-provided credentials in the secret file.

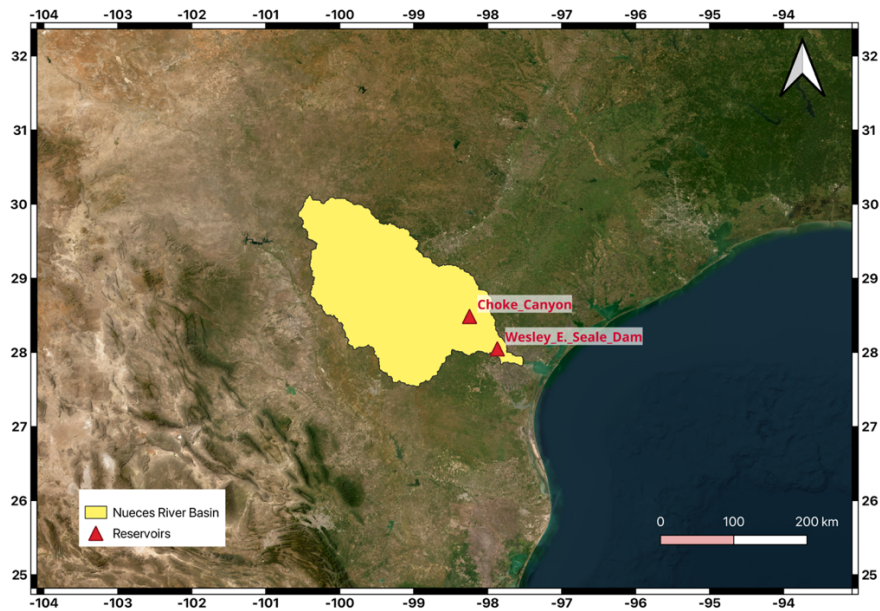


Figure 3.3 Map of the Nueces River basin in USA, showing location of the reservoirs used for test case.

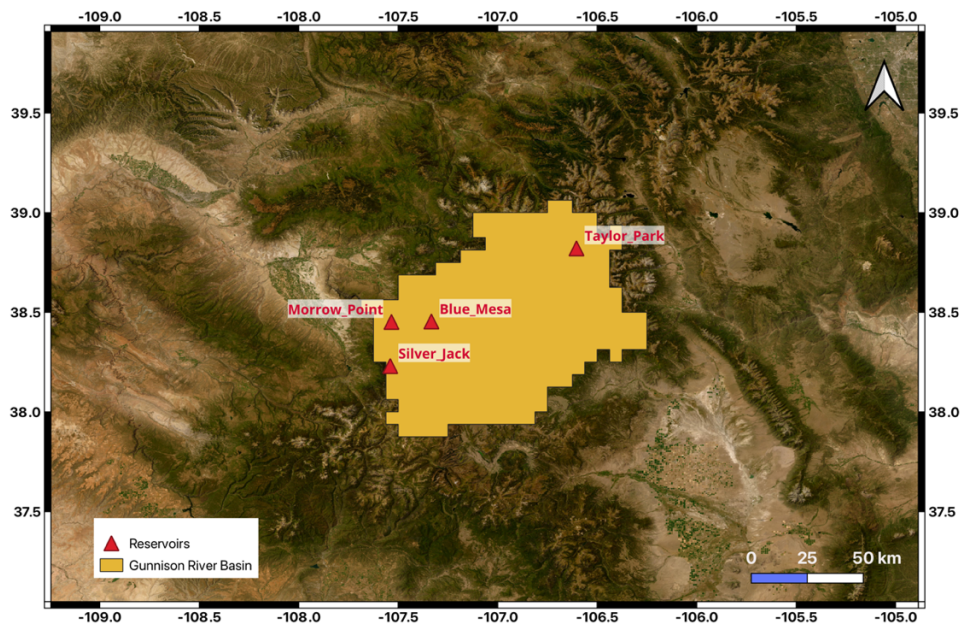


Figure 3.4 Map of the Gunnison River basin in USA, showing location of the reservoirs used for test case.

3.4.3. Execution

To run RAT through the command-line interface, one can utilize the 'rat run' command by specifying its configuration file. It also offers users the option to run RAT in an operational mode, which means that RAT will resume from the last state of a previous run, commencing execution from the end date of that prior run. Moreover, executing and operationalizing RAT can also be accomplished through Python scripts for more flexibility and customization.

3.4.4. Configure

Given that the RAT configuration file contains numerous parameters, many of which may prove perplexing for beginners while being useful for advanced users, there exists a 'rat configure' command. This command automatically fills in specific parameter values in the configuration file using user-provided options like the number of CPU cores to use and the secret file path. If users have downloaded the global database, they can provide the path of this database to set default values to a lot of parameters in the configuration file, enhancing convenience and clarity.

3.4.5. Toolbox

A 'toolbox'-named module has been developed and added to the library that can be accessed in Python. The purpose of this toolbox is to provide utility functions that make it easy to access and use RAT. It is now possible to update RAT's configuration file from within Python with just one line of code. It is especially useful when RAT needs to be executed in iterations, for example, while calibrating the VIC model. It also provides functionality to compare RAT estimates with in-situ data or data from other sources with different metrics like Nash-Sutcliffe Efficiency (NSE)(Nash & Sutcliffe, 1970) and Kling-Gupta Efficiency (KGE)(Gupta et al., 2009). With the toolbox, users can now also create interactive visualizations for the time-series of different variables like inflow, outflow, and storage-change.

3.4.6. Plugins

With the introduction of the RAT library, it is now convenient for the developing community of RAT to create and add plugins to the existing framework of RAT. These plugins can be built to cater to the different needs of the water community. One of the recent plugins that has been

developed for RAT is Reservoir Operations driven River Regulation abbreviated as ResORR (Das et al., 2024). ResORR is a model that accounts for regulation of rivers due to upstream reservoir operations in the estimation of downstream reservoir inflow and outflow. It is scalable and can be applied globally as it requires minimal parameterizations and uses satellite data along with intermediary outputs of RAT.

Another plugin that has been developed for RAT provides up to 15 days of forecasted inflow for any reservoir worldwide using weather forecasts. It is helpful for tracking extreme flood events and can provide water managers with a chance to better handle the water level in reservoirs. Even though RAT can account for the changing bathymetry of a reservoir due to sedimentation if a survey-based in-situ Area-Elevation Curve (AEC) is provided, there is no inherent way to know how much storage has been lost due to the trapping of sediments in the reservoir. Research is ongoing to develop a plugin for RAT that can give some insight into storage loss due to reservoir sedimentation using remote sensing data.

3.5. Maintenance of the Python Library

3.5.1. Documentation

As thorough and up-to-date documentation is a key component of any Conda library, a comprehensive and meticulous documentation is readily available and continually maintained at two URLs^{2,3}. This documentation serves as a valuable resource for users of RAT, offering a user-friendly guide for swift and trouble-free installation. Within this documentation, users will find a wealth of information, including:

- **User Guide:** This guide simplifies the installation process for the RAT Python package, making it quick and accessible.
- **Command Line and Python Interface:** Instructions on how to use the command line interface of RAT to initialize and verify the successful installation of the package are

² <http://ratdocs.io>

³ <https://rat-satellitedams.readthedocs.io/>

provided. Commands that can be used in Python to execute RAT and analyze results are also listed.

- **Directory Structure:** Details about the directory structure created by RAT, along with guidance on locating data files generated by the RAT tool.
- **Global Datasets:** Descriptions of the global datasets included with RAT for user convenience.
- **Model Architecture:** A comprehensive exploration of the model's architecture is found in the 'Computational Model' section, while the 'Conceptual Model' section elucidates the theoretical model.
- **Configuration Parameters:** Each configuration file parameter is explained, including its necessity, description, and required syntax.
- **Developer Guide:** Easy guide summarizing how to use the developer version for new developers who want to contribute towards the improvement and enhancement of the software.

Furthermore, the documentation not only covers the creation and acquisition of various credentials needed for successful RAT execution but also offers guidance on consolidating them into a single 'secrets' file.

This documentation plays a pivotal role in democratizing access to information regarding the dynamic state of reservoirs and acts as the main guide for developers to contribute to the source code of RAT. The authors encourage contributions from the community and the reporting of issues faced⁴. The discussion forum⁵ is dedicated to support the user community of RAT.

3.5.2. Continuous Integration / Continuous Development (CI/CD) pipeline

⁴ <https://github.com/UW-SASWE/RAT/issues>

⁵ <https://github.com/UW-SASWE/RAT/discussions>

Continuous Integration and Continuous Deployment (CI/CD) pipelines are essential for scientific software development as they ensure code quality, reproducibility, and efficient distribution of research tools. In scientific computing, where results must be verifiable, and software must be reliable, automated testing and deployment processes help maintain high standards while allowing researchers to focus on scientific work rather than technical overhead.

The RAT software exemplifies this best practice through its CI/CD pipeline, implemented using GitHub Actions. When a new release is created, the pipeline initiates an automated build process to package the RAT software as a Python package. This is followed by a suite of tests to confirm the functionality and reliability of the code. Once the tests are successfully completed, the package is published to the Python Package Index (PyPI), making it immediately available to the scientific community. The PyPI is a repository of software for the Python programming language, where users can find and install Python packages for their projects. Eventually the RAT package is published to the conda-forge, a widely used repository for Conda packages across the scientific community.

The pipeline further enforces stringent quality control for code contributions. Whenever new code is pushed, the test suite runs automatically. Only if all tests are successful will the updated package be published, requiring developers to resolve any issues beforehand. This process ensures that users consistently have access to the latest stable and thoroughly tested version of RAT, while reducing the likelihood of errors in the deployment process.

3.6. Application of the Python Library

This section demonstrates how the RAT 3.0 library can be used not only to accelerate and conduct research analysis but also has significant potential for water managers to understand surface water availability where ground-based data is not available. For this application, RAT 3.0 has been applied in the Krishna River Basin in India. To keep the scope of this application small, only single dam has been selected which is the Hidkal Dam, also known as, Raja Lakhamagouda Dam (Figure 3.2).

There is no doubt that heavy and erratic rainfall is one of the reasons for floods in several parts of the world. However, that is often coinciding with dams being full due to poor management, resulting in dam-induced floods (Suresh et al., 2024; Kundu & Mothikumar, 1995 and Zhang et al., 2014). In the first week of August 2019, due to heavy rainfall in the Monsoon season, a severe flood affected the southern Indian state of Karnataka. Thousands of people were evacuated to safer places and relief camps. One of the districts that was drastically affected by these floods was Belagavi district where the Hidkal Dam is located. It is speculated that the dam worsened the impact of floods. Thus, this application of RAT attempts to verify the role of the Hidkal Dam in the Karnataka floods of 2019.

3.6.1. Study Area

The Hidkal Dam, located on the Ghataprabha River—a tributary of the Krishna River—in Karnataka, India, serves as a critical resource for irrigation, drinking water supply, and hydropower generation. The Krishna River Basin, one of the largest river basins in India, spans diverse climatic and geographical conditions, making it an excellent test site for evaluating the RAT library.

The Hidkal Dam was chosen for this study due to the availability of historical inflow and outflow data and the absence of upstream dams, ensuring minimal interference in the inflow. Thus, ResORR is not required for this study to estimate inflow. The dam's catchment area covers approximately 1,370 km² and is characterized by highly undulating terrain, with elevations ranging from 1,049 m to 640 m above sea level. The region receives most of its rainfall between June and September, with annual precipitation varying significantly from 1,000 mm to 6,250 mm. Additionally, the mean annual temperature in the catchment fluctuates between 20°C and 40.5°C, reflecting the basin's diverse climatic conditions (Rao et al., 2024).

3.6.2. Setting Up

RAT 3.0 was installed and initialized using Conda along with the global database (Minocha et al., 2024). The shapefile delineating the Krishna River basin was sourced from the Global Runoff Data

Centre's (GRDC) river dataset (GRDC, 2020), while the shapefiles for the Hidkal dam and reservoir were obtained from the Global Reservoir and Dam Database (GRanD) v1.3 (Lehner et al., 2011). Both datasets are provided as part of RAT's global database.

The different service accounts required to execute RAT 3.0 were established and the credentials were consolidated into a single secrets file (Example 1 is shown with placeholder data). To set up the required accounts and obtain the credentials, users can refer to the RAT documentation⁶. Essential parameters, including the number of cores for RAT's multiprocessing mode, execution steps, and the specified start and end dates, were defined in RAT's configuration file (0 , Section 10.1). Subsequently, RAT was executed based on the configured settings, covering a one-year duration from January 1, 2019.

To run RAT for any other area, users can modify the parameters in the configuration file, which are explained with comments in the code block in (0 , Section 10.1).

```
##### This is a template for a file (.ini format) that contains credentials #####
##### to various accounts used by RAT to download and process data #####

## Please create the following accounts in order to successfully use RAT 3 ##
#To create an AVISO account (for Jason 3 altimetry data), use this link
"https://www.aviso.altimetry.fr/en/data/data-access/registration-form.html"
#To create an IMERG account (for global precipitation data), use this link
"https://registration.pps.eosdis.nasa.gov/registration/"
#To create a service account (for using google earth engine), use this link
"https://developers.google.com/earth-engine/cloud/earthengine_cloud_project_setup"

#Enter user credentials (email, password) for aviso
[aviso]
username= xyz@gmail.com
pwd= ****
```

⁶ <https://rat-satellitedams.readthedocs.io/en/latest/QuickStart/GettingReady/>

```
#Enter user credentials (email, password) for imerg
[imerg]
username= xyz@gmail.com
pwd= ****

#Enter service account (account_email, path to private json key) for google earth engine
[ee]
service_account= xyz@project.iam.gserviceaccount.com
key_file= path/to/private/key.json
```

Example 1: The secrets.ini file used to run RAT (shown with placeholder data). Users must provide their AVISO, IMERG, and EE credentials.

3.6.3. Inflow

The inflow into the Hidkal reservoir was simulated for the entire year of 2019 at a daily time step and subsequently compared against in situ data obtained from the Karnataka Water Resources Department (Figure 3.5). The peak flood duration is shown in green in Figure 3.5. In particular, the model accurately identified the peak inflow during the flood on August 8 and 9. However, the model indicated a substantial offset in the magnitude of the peak, suggesting a potential underestimation in the rainfall dataset used (IMERG) as it is difficult to achieve such a high offset even by calibrating the VIC model. Although the calibration of the VIC model was attempted, it failed to make any significant improvement in flood-peak accuracy. Consequently, the uncalibrated inflow data were used to generate Figure 3.5. Users can calibrate their model by referring to the VIC documentation⁷. Despite the magnitude offset, the model's ability to precisely capture the onset and recession times of the flood event, as demonstrated by Suresh et al. (2023), underscores RAT's capability to effectively track such events using solely satellite data.

⁷ <https://vic.readthedocs.io/en/vic.4.2.d/Documentation/Calibration/>

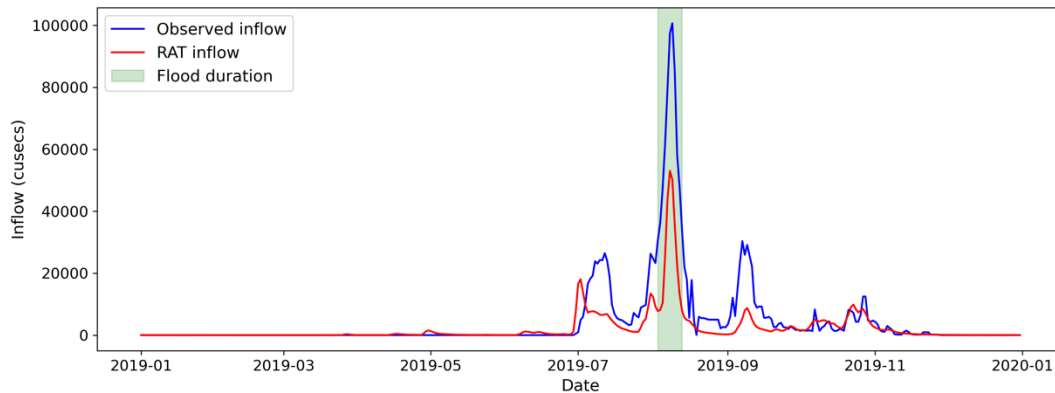


Figure 3.5 The timeseries of inflow (measured in cubic feet per second) into the Hidkal Reservoir throughout the year 2019. The peak flood duration is highlighted in greenish color.

3.6.4. Surface Area

RAT tracked the surface area of the reservoir using the Google Earth Engine (GEE) Python API from the start of the year 2019 to the end of 2019 (Figure 3.6). The surface area estimates were generated using the Tiered Multi Sensor-Optical and SAR (TMS-OS) algorithm at a frequency of 2 to 5 days. As satellite remote sensing data is often recognized for identifying qualitative trends due to potential bias issues, the trend of the reservoir level has been accurately picked by RAT. The reservoir level was lowered from March to June which is the pre-monsoon period in South Asia. This standard practice is typically employed to accommodate the anticipated high inflows during the monsoon, allowing the reservoir to reach its full capacity by the end of the monsoon season. However, in this particular case, the reservoir was almost completely filled by early August, which is only halfway through the monsoon.

3.6.5. Evaporation

The amount of evaporation from the reservoir was estimated by RAT using the Penman's equation at a daily frequency (Figure 3.7). At the time of the flood peak, the evaporation was very low which was probably due to the high humidity in the air in that region.

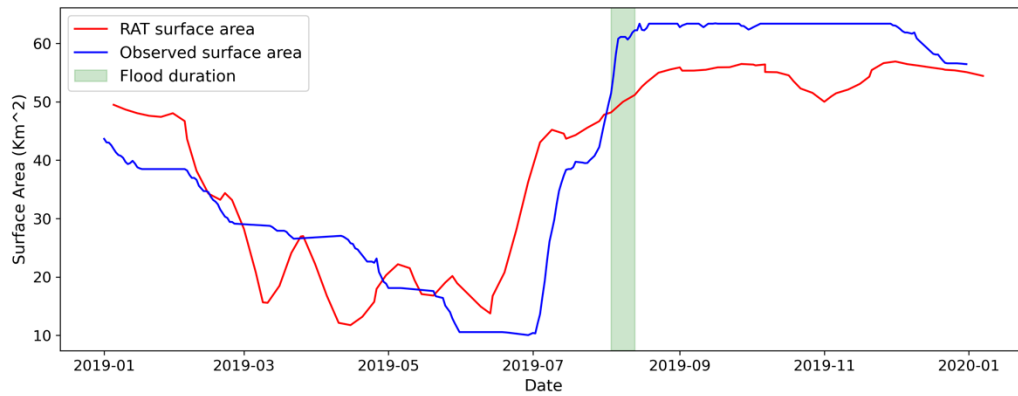


Figure 3.6 The timeseries of surface area (measured in km²) of the Hidkal Reservoir throughout the year 2019. The peak flood duration is highlighted in greenish color.

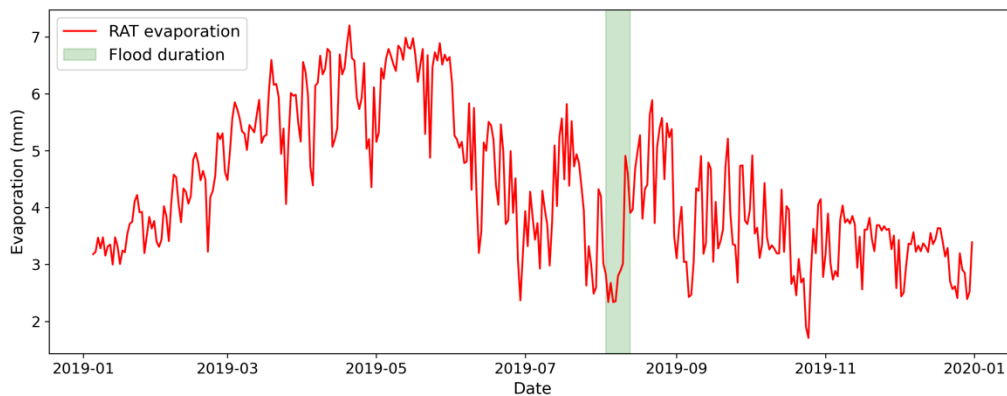


Figure 3.7 The timeseries of evaporation (in mm) from the Hidkal Reservoir throughout the year 2019. The peak flood duration is highlighted in greenish color.

3.6.6. Area-Elevation Curve

RAT constructed the Area-Elevation Curve (AEC) for the Hidkal reservoir (Figure 3.8) by leveraging the SRTM digital elevation model available in Google Earth Engine (GEE), as no survey-observed AEC was provided as input (Farr et al., 2007). Since SRTM data were recorded in 2000 whereas the reservoir was created before 2000, it does not have elevation data below the reservoir level at the time SRTM was recorded. RAT 3.0 therefore extrapolates the AEC for lower reservoir levels. Users are advised to utilize the most recent in-situ AEC data whenever available,

to enhance the precision of storage change and outflow estimations derived from RAT. In general, bathymetric survey-based AECs are the most reliable.

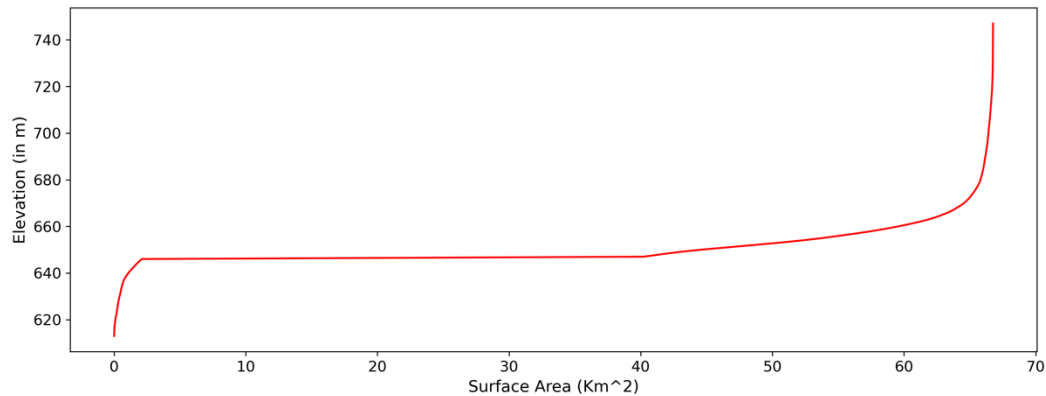


Figure 3.8 The Area Elevation Curve (AEC) for the Hidkal Reservoir generated by RAT 3.0 using SRTM digital elevation model.

3.6.7. Outflow

The estimation of outflow from the Hidkal Dam involves utilizing the mass balance approach, which considers inflow, storage change, and evaporation. RAT calculates storage change using surface area estimates and the Area-Elevation Curve (AEC), resulting in an outflow temporal frequency matching that of surface area estimates. While the mass balance approach incorporates uncertainties from each component, the lower temporal frequency further amplifies these uncertainties. Despite these challenges, RAT successfully identifies the timing of the peak outflow during the flood event (Figure 3.9). The considerable difference in the magnitude of the peak outflow, compared to in-situ measurements, is primarily attributed to the underestimation of inflow at that particular time. Figure 3.5 and Figure 3.9 illustrate a noticeable offset in the magnitude of the estimated peak inflow and outflow when compared to in-situ data, indicating a consistent level of discrepancy.

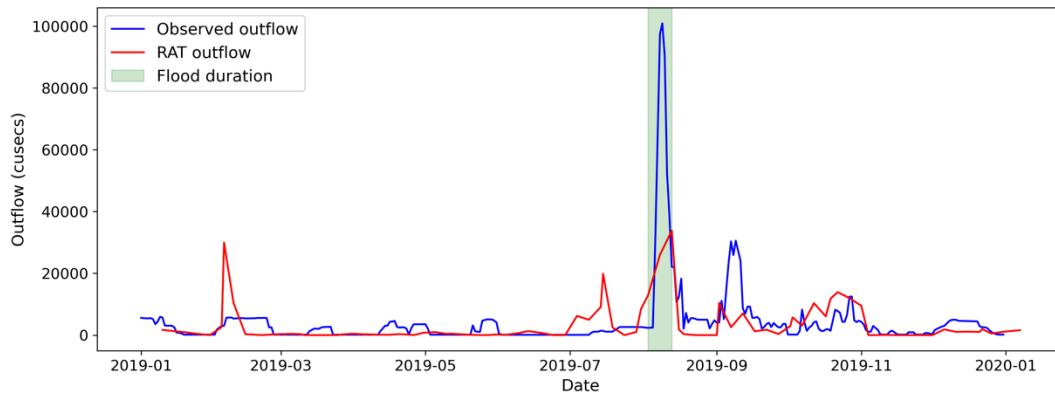


Figure 3.9 The timeseries of outflow (measured in cubic feet per second) from the Hidkal Reservoir for the year 2019. The peak flood duration is highlighted in greenish color.

The above application shows that RAT was able to capture the timing of the onset and recession of the flood (Figure 3.5). It was also able to track the reservoir level during the flood. With this analysis, it can be noticed that the reservoir was filled almost to its maximum capacity when there was still half of the monsoon period left (Figure 3.6). This forced the dam operators to release all the water that the reservoir was getting during the flood, leaving no scope for managing the floodwater (Figure 3.9). This can be verified by looking at the ratio of the RAT-generated estimates of inflow and outflow.

3.6.8. Performance Analysis

To evaluate the performance of RAT, we computed the Nash-Sutcliffe Efficiency (NSE) (Nash & Sutcliffe, 1970), Kling-Gupta Efficiency (KGE) (Gupta et al., 2009), Normalized Root Mean Square Error (NRMSE), and Pearson Correlation for inflow, outflow, and surface area estimates by comparing them with in-situ data (Table 3.3). NRMSE was expressed as a percentage by normalizing the RMSE with the range of observed values. While surface area is not a direct hydrologic flux, it serves as a key response variable influenced by inflows and outflows. Therefore, assessing RAT's performance using NSE, KGE, and correlation for surface area provides valuable insights into its capability to track hydrologic variations and reservoir dynamics.

The results indicate moderate agreement for inflow (NSE = 0.567, KGE = 0.229, Correlation = 0.901) and surface area (NSE = 0.777, KGE = 0.771, Correlation = 0.89), whereas outflow estimates exhibit lower agreement (NSE = 0.221, KGE = 0.314, Correlation = 0.485). The lower accuracy in outflow estimation is likely due to the poor-quality Active Elevation Curve (AEC) generated by SRTM, as discussed in Section 3.6.6.

While RAT proves to be highly useful for qualitative assessments, such as tracking the onset and recession of flood events and can estimate inflows and surface area with moderate accuracy using satellite data, there is room for improvement of its outflow estimation by incorporating higher-quality in-situ AEC data.

Table 3.3 Performance metrics for RAT estimates of inflow, outflow, and surface area compared to in-situ data for the Hidkal Reservoir.

Metric	Inflow	Outflow	Surface Area
NSE	0.567	0.221	0.777
NRMSE	7.92 %	10.25 %	16.79 %
Correlation	0.9	0.49	0.89
KGE	0.229	0.314	0.771

3.7. Conclusions and Discussion

With increasing global reliance on dams and reservoirs, surface water availability is determined by a complex interaction of natural processes and human decisions. Human control, particularly in terms of reservoir operations, plays a critical role in influencing the quantity of surface water available in any region. Therefore, it is important to monitor reservoir operations. However, monitoring these operations on a global scale remains challenging due to the high costs associated with conventional monitoring tools. Satellite remote sensing offers a cost-effective alternative by providing real-time global data.

The Reservoir Assessment Tool (RAT) is a remote-sensing based reservoir monitoring tool that provides data on reservoir dynamics, including inflow, outflow, storage change, evaporation, and surface area, at a frequency of 2-5 days. A recent upgrade in the software architecture of RAT 3.0 has brought significant improvements in enhancing computational and memory efficiency, ease of use, computational robustness, and global scalability. Despite these advancements, there remains the challenge of time-consuming installation and setup for first-time users, as well as a lack of a systematic method to verify correct installation. To continuously evolve as a software package, RAT also requires a dedicated forum to archive new versions for users to upgrade. Additionally, the developer community needs a proper pipeline to automatically verify the correctness of their contributed code and ensure improvements to the software.

To address these challenges, RAT 3.0 has been packaged as a Python library designed to streamline the installation process and enhance the user experience, particularly for first-time users. The Python library is created using the Conda package manager that also acts as the channel for users to easily upgrade the library to the latest version available. It is hosted on the conda-forge repository, where most of the open-source Conda packages are available. As of the time of writing this manuscript, the library has been downloaded over 9700 times, with 70-80% of the downloads coming from non-developers. Packaging RAT 3.0 using Conda has also proven beneficial for distributing it as a command line utility tool. Various command line functions have been added to increase the tool's versatility. It is now also possible to install the complete VIC hydrological model along with its components, MetSim and routing, using a single command.

The installation of RAT 3.0 can now be easily verified by users through two test river basins, ensuring smoother installation for first time users. These tests are also instrumental in verifying code contributions from the development community. Additional command line functions, such as 'configure' (which partially auto fills a configuration file) and 'run' (which executes RAT with a configuration file), further enhance the tool's usability. With the release of the Python library, it is now easier for developers to create and add plugins to RAT 3.0, expanding its functionality. A user-friendly toolbox has also been added as a component to facilitate tasks such as configuration

file creation and updates, interactive visualization of RAT outputs, and error computation between estimated and in-situ data using various error metrics.

Along with the Python library, efforts have been made to maintain and keep it updated. Continuous Integration / Continuous Development (CI/CD) pipeline has been established using GitHub actions that automatically verifies the working of the software after incorporating the contributed code by the developers, creating new versions when tests are passed. A detailed and thorough documentation has also been prepared and hosted online. It not only aids users but also serves as a resource for developers to understand the code and contribute to its improvement.

The paper also showcases RAT's ability to track the onset and offset of the flooding using only remote-sensing data. It also shows how RAT can track the reservoir level or its surface area before and during the flood, which can shed light on the role of dam operations in flood-related damage. However, RAT's applications extend beyond extreme events like floods and droughts. It provides a framework for incorporating reservoir dynamics into climate models, offering a data driven approach to understanding global reservoir operations. The availability of surface water and how much of that is being lost due to evaporation can also be tracked using RAT.

While the tool has certain limitations in terms of the precision of quantitative analysis, calibration with in-situ data can increase accuracy. Substituting estimated inflow or surface area/reservoir level with the observed data can reduce uncertainties in outflow estimates. Using AECs based on the latest bathymetry of the reservoir, which accounts for storage loss due to sediment trapping, can further improve estimations.

With the Python library in place, the community is now equipped to address these limitations and continuously improve the software. New and advanced satellite missions, like Surface Water and Ocean Topography (SWOT), can be incorporated to improve the accuracy of the surface area estimates, which can further improve the estimation of outflow from the reservoir. Moreover, plugins can be developed to provide additional insights into aspects like sediment trapping

efficiency, rule-curves, and water quality. The important thing to note is that the infrastructure, forum, and pipeline for open-source, satellite-based reservoir monitoring is now established, enabling global, continuous improvements to the RAT software by anyone, anywhere in the world.

Monitoring reservoir dynamics is, however, only one side of the sustainability challenge. The deeper and ultimately irreversible threat is sedimentation—the gradual infilling of reservoir storage that neither improved software nor better satellite coverage can reverse once it has occurred. Addressing that threat scientifically requires reliable, globally consistent ground-truth data on how much capacity has already been lost, and at what rate. Such a dataset did not exist in any open, curated form. Chapter 4 describes the construction of GRILSS—the Global Reservoir Inventory of Lost Storage by Sedimentation—the first openly accessible, consistently curated dataset of sedimentation rates and capacity loss spanning over 1,000 reservoirs across 75 major river basins, thereby laying the empirical foundation that the chapters that follow depend on.

Chapter 4. GRILSS: Opening the Gateway to Global Reservoir Sedimentation Data Curation

Note: This chapter has been published in its current form in *Earth System Science Data*. The only differences are in the numbering of figures, tables, and references to other sections. [Publication: Minocha, S. and Hossain, F., 2025. GRILSS: Opening the gateway to global reservoir sedimentation data curation. *Earth System Science Data*, 17(4), pp.1743-1759. <https://doi.org/10.5194/essd-17-1743-2025>]

4.1. Abstract

Reservoir sedimentation poses a significant challenge to freshwater management, leading to declining storage capacity and inefficient reservoir operations for various purposes. However, trustworthy and independently verifiable information on declining storage capacity or sedimentation rates around the world is sparse and suffers from inconsistent metadata and curation to allow global-scale archiving and analyses. The **Global Reservoir Inventory of Lost Storage by Sedimentation (GRILSS)** dataset addresses this challenge by providing organized, well-curated and open-source data on sedimentation rates and capacity loss for 1,015 reservoirs in 75 major river basins across 54 countries. This publicly accessible dataset captures the complexities of reservoir sedimentation, influenced by regional factors such as climate, topography, and land use. By curating the information from numerous sources with disparate formats in a homogenized data structure, GRILSS serves as an invaluable resource for water managers, policymakers, and researchers for improved sediment management strategies. The open-source nature of GRILSS promotes collaboration and contributions from the global community to grow the dataset. By providing essential reference data on sedimentation to understand the global challenge of reservoir sedimentation, this GRILSS dataset represents a gateway for the global community to share sedimentation and storage loss data for sustainable operation of world's reservoirs for future generations.

4.2. Introduction

Artificial reservoirs created by damming a river or a lake are essential components of modern water management systems. Such reservoirs provide critical freshwater resources for irrigation, domestic and industrial use, as well as generate hydropower and moderate floods (McCully, 1996). However, these dams and their reservoirs pose significant environmental challenges (Nguyen et al., 2024), including the destruction of ecosystems (Tundisi, 2018), loss of biodiversity (Wu et al., 2019), disruption of aquatic life (Morley, 2007), greenhouse gas emissions (Tran et al., 2023), and barriers to fish migration (Pelicice et al., 2015). Despite these drawbacks, numerous reservoirs remain in operation, as they can fulfill multiple essential functions for society. As dams age, the effectiveness of reservoirs becomes increasingly compromised by sedimentation, which gradually reduces their water storage capacity and threatens their long-term functionality (Kondolf et al., 2014 and Wisser et al., 2013).

Hereafter, the terms dam and reservoir will be used interchangeably as shorthand for the dam-reservoir system. Despite the ongoing planning and construction of new dams worldwide (Zarfl et al., 2015), global reservoir capacity peaked in 2006 and has apparently been declining ever since (Wisser et al., 2013). This paradox is primarily due to the accumulation of sediment at the bottom of reservoirs, which gradually reduces their storage capacity. Wisser et al. (2013) estimated that global per capita reservoir capacity declined by 19% between 1987 and 2010, and when sedimentation is factored in, the decrease is even more pronounced at 21%. Moreover, most of the optimal sites for dam construction have already been utilized, and the remaining feasible locations are often less economical (Morris & Fan, 1998). As a result, the new dams being built are generally smaller (Demirbas, 2009), and the rate of construction is not keeping pace with the rate of sedimentation. Overall, the current trend highlights the pressing need to address reservoir sedimentation to ensure a sustainable supply of freshwater for energy, food and flood control for future generations.

Regaining the storage capacity lost to sedimentation is essential for halting the global decline in reservoir capacity without having to build costly, uneconomical and ecosystem-damaging newer dams. One of the primary solutions is to implement sediment management techniques, such as sediment flushing, dredging, and watershed management, which requires a thorough

understanding of sedimentation rates in reservoirs worldwide (Morris, 2014; Kondolf et al., 2014; George et al., 2017). Since sedimentation rates vary depending on regional factors, conducting localized studies is crucial for accurately assessing these rates. Topography, geology, vegetation and precipitation can affect the rate of soil erosion which can further affect sedimentation rates and consequently the rate of storage capacity loss. Due to the interplay of vast number of other factors such as operation procedure, reservoir shape and purpose, sedimentation rate can also be significantly different from one neighboring reservoir to another.

Sedimentation rates in reservoirs can be estimated using either direct or indirect methods (Nyikadzino & Gwate, 2021). Direct methods, such as bathymetric surveys, involve measuring the reservoir's depth over time and comparing the surveys to estimate storage loss, which is attributed to sediment deposition. These methods tend to be most accurate but are also more costly (Samaila–Ija et al., 2014; Patil et al., 2015). On the other hand, indirect methods use satellite remote sensing or numerical modeling to estimate sedimentation rates (Elçi et al., 2009; Hanmaiahgari et al., 2018; Pandey et al., 2016; Zhang et al., 2006). While indirect methods are less expensive, they rely on the availability of in-situ data, such as soil moisture and soil type for numerical models, or reservoir water elevation data, often obtained through in-situ or altimetry-based measurements, for remote sensing applications (Ghosh et al., 2024; de Oliveira Fagundes et al., 2020; Dutta, 2016).

Due to these limitations, only a small fraction of the world's millions of reservoirs have been thoroughly assessed or gauged for sedimentation rates, and even fewer are well-documented in published literature. Countries like the United States and India have made efforts to compile sedimentation databases for a limited number of reservoirs within their national boundaries (Gray et al., 2010; Central Water Commission, 2020). However, despite these initiatives, there remains no comprehensive, well-documented global dataset on reservoir sedimentation rates or storage capacity loss. While numerous regional studies have analyzed sedimentation rates for individual reservoirs, a unified, well-curated and publicly available global dataset capturing sedimentation rates and available storage capacity across the world remains absent. This lack of a cohesive data archive for the global community presents a major challenge in addressing and understanding

reservoir sedimentation on a global scale (Syvitski et al., 2003; Vanmaercke et al., 2011; Wisser et al., 2013; Perera et al., 2023).

In this paper, we address the need for a comprehensive, consistently curated and publicly available dataset that compiles the loss of storage capacity due to sedimentation in reservoirs worldwide. We introduce Global Reservoir Inventory of Lost Storage by Sedimentation (GRILSS; Minocha & Hossain, 2025) dataset, the first open-source dataset of its kind, to the best of our knowledge. GRILSS includes information on over 1,000 reservoirs, detailing the amount of sedimentation and lost capacity over specific time intervals along with various meta data details. Additionally, GRILSS provides other attributes such as the height of impoundment, catchment area, and original built capacity of the reservoirs, where available.

GRILSS has the potential to be highly valuable for the global freshwater community, offering insights into sedimentation patterns in reservoirs around the world. By providing sedimentation rates and their variations across different river systems, GRILSS can potentially enhance our understanding of how sedimentation processes differ regionally. GRILSS can inform sediment management strategies by identifying how these techniques should be tailored to specific regions. As the first version of its kind, we anticipate that GRILSS will continue to grow over time, both in size and use, with future contributions on sedimentation data from the global community to expand the global coverage of reservoirs.

4.3. Dataset Preparation

4.3.1. Collection of sedimentation data

The GRILSS dataset (Minocha & Hossain, 2025) was compiled through an extensive literature review of published articles, theses, government documents, and websites, some of which were in languages other than English (Estrada et al., 2015). The literature review was not completely systematic. Search engines such as Google, Google Scholar, and ResearchGate were utilized with

keywords like "reservoir capacity loss," "reservoir sedimentation," "bathymetric surveys," and "sedimentation rate," among others. Conducting a fully systematic review proved challenging due to the inclusion of grey literature, which is often not indexed in standard databases or publicly accessible. After carefully reviewing hundreds of papers and documents, the dataset was created by manually compiling data from 143 different sources using Microsoft Excel. Only sources containing specific sedimentation data related to reservoirs were included. This thorough process ensured that the dataset covers sedimentation information from a wide range of regions.

Since sedimentation can be reported in various ways, we tracked metrics from different sources. Many sources directly provided sedimentation amounts in million cubic meters (MCM) along with the duration over which the sedimentation occurred. However, some sources reported sedimentation in million tons (MT) (Kim et al., 2014; Palinkas & Russ et al., 2019). Additionally, certain sources mentioned the percentage of capacity loss over a specific period but did not always include the reservoir's original capacity (Güvel, 2021; Patro et al., 2022). A few sources only provided the sedimentation rate (either in MCM or MT), with or without specifying the time frame used to calculate it (Lorsirirat, 2014; Yang et al., 2022). Due to this variability in reporting, the GRILSS dataset had to be carefully compiled and standardized to ensure consistency of data structure across the dataset (Minocha & Hossain, 2025).

For sources where the sedimentation amount was reported in million tons (MT), the bulk sediment density was obtained either from the same source or a comparable source for that region. Using this bulk density, the sedimentation volume was then estimated in million cubic meters (MCM) with the help of Eq. (4.1). In cases where only the sedimentation rate was available, the rate was assumed to represent the sedimentation amount over a one-year period using Eq. (4.2). Unless otherwise specified, this duration was assumed representative from two years before the source's publication date to one year afterwards. For other reservoirs, the sedimentation rate was also estimated using Eq. (4.2).

$$\text{Sedimentation volume (MCM)} = \frac{\text{Sediment weight (MT)}}{\text{Bulk sediment density} \left(\frac{\text{ton}}{\text{m}^3} \right)} \quad (4.1)$$

$$\text{Annual sedimentation rate} \left(\frac{\text{MCM}}{\text{year}} \right) = \frac{\text{Sedimentation volume (MCM)}}{\text{Time Duration (year)}} \quad (4.2)$$

For cases where sedimentation was reported as a percentage of capacity loss, but the reservoir's original capacity was not provided, the initial capacity was extracted from other datasets or references. The sedimentation volume was then calculated using Eq. (4.3). Equation (4.3) was also used to calculate the percentage of capacity loss when sedimentation volume and original built capacity were available. The annual rate of reservoir capacity loss, expressed as a percentage of the original built capacity was estimated for all reservoir using Eq. (4.4). This approach ensured consistency in estimating sedimentation volumes, annual sedimentation rates, and capacity loss percentages across various reporting formats. However, sedimentation weight in million tons (MT) was not estimated for all reservoirs due to insufficient bulk sediment density data.

$$\text{Sedimentation volume (MCM)} = \frac{\% \text{ Capacity loss} * \text{Original built capacity (MCM)}}{100} \quad (4.3)$$

$$\text{Annual capacity loss rate} \left(\frac{\%}{\text{year}} \right) = \frac{\% \text{ Capacity loss}}{\text{Time Duration (year)}} \quad (4.4)$$

In the context of sedimentation volume, it should be noted that this is typically derived by comparing reservoir bathymetry data collected at two different times. The capacity lost is attributed to the sedimentation caused by sediment transport from the catchment and deposition within the reservoir. While this approach assumes sedimentation volume is primarily from catchment-derived input, it does not account for sedimentation resulting from the transport of sediments within the reservoir itself, including processes like the retreat of reservoir banks. Future studies addressing sedimentation dynamics should explicitly consider such cases when relevant.

While efforts were made to standardize sedimentation data through conversions and assumptions, such as assuming a one-year sedimentation period when not specified or estimating bulk sediment density, these approaches inevitably introduce uncertainties. It is important to note that the assumption of a one-year sedimentation period affects essentially sedimentation volume calculations and not sedimentation rates. Thus, sedimentation rates should be used for inter-reservoir comparisons. The reliance on such assumptions reflects the limitations of the available data and underscores the need for more robust and consistent reporting practices globally. Consequently, trends and comparisons derived from these data should be interpreted with caution.

For consistency and accuracy in reporting reservoir sedimentation data, we recommend the inclusion of minimum key metrics for each reservoir. These should include the sedimentation volume in million cubic meters (MCM) and the time frame over which sedimentation occurred. Additionally, it is important to indicate whether the reservoir employs any sediment management techniques. Key dam attributes such as the original built capacity, construction year, and precise dam coordinates should also be reported. Although variations in the spelling of reservoir names may arise across different sources, the inclusion of coordinates offers a unique and reliable method for identifying and comparing reservoirs, thus improving data consistency and reliability in future studies.

4.3.2. Collection of reservoir attributes

From each source, the reservoir name and the country of location were extracted and manually compiled in Microsoft Excel along with the sedimentation data. Other reservoir attributes, such as impoundment height, year of construction, original capacity, and catchment area, were also recorded when available.

While geospatial coordinates of the reservoir were rarely provided from most sources, they were included in the GRILSS dataset whenever available. In many cases, sources provided only a figure showing the approximate location of the reservoir, making it difficult to derive precise geospatial

coordinates. Additionally, some sources provided only the extent of the reservoir rather than the exact coordinates of the dam impoundment. Out of the over 1,000 reservoirs for which data was collected, only around 170 had geospatial coordinates of the dam.

Since a reservoir database without georeferencing is of limited utility for analyses, addressing the challenge of mapping the reservoir attributes to their corresponding dam locations became crucial. To accomplish this, the Global Dam Tracker (GDAT), which contains more than 35,000 georeferenced dams with attributes, was utilized (Zhang & Gu, 2023). The reservoir names in GRILSS were fuzzy-matched to the dam names in GDAT using the Python library "thefuzz" (Seatgeek, 2021). This method was used to account for minor variations in the spelling of reservoir names across different regions, where slight differences in spelling could prevent a direct match.

For each reservoir in the GRILSS dataset, the top 10 dam name matches, based on fuzzy-matching scores, were extracted from the GDAT dataset. Since there could be multiple dams or reservoirs with the same name, a manual review of the matches was conducted. This involved comparing other attributes such as year of construction, original capacity, and country for both datasets to ensure consistency. If these attributes aligned, the match was confirmed. Through this process, we successfully identified the corresponding dams for 613 GRILSS reservoirs from the GDAT dataset.

In cases where attributes like impoundment height, year of construction, or original built capacity were missing in GRILSS but available in GDAT, these values were added to the dataset. However, geospatial coordinates were not always available, even for dams listed in GDAT. For all remaining reservoirs lacking dam coordinates, geospatial data was manually derived using Google Earth and Google Maps, by searching for the reservoir name in the specified region as indicated by the original source. When approximate location maps were available, these figures were overlaid on actual maps with proper scaling to accurately determine the impoundment locations. Through this process, all reservoirs in the GRILSS dataset were successfully georeferenced (Minocha & Hossain, 2025).

4.3.3. Collection of other attributes

To increase the utility of GRILSS, additional attributes were added to the dataset. One key attribute added from each source was the method used to estimate sedimentation for a given reservoir, categorized into three main types: (1) bathymetric survey, (2) remote sensing, or (3) numerical modeling.

- 1 Bathymetric survey (BS): This method involves repeating a survey after a specific time period and comparing it with previous surveys. The observed loss in reservoir capacity is attributed to sedimentation volume (Stauch et al., 2024; Ugwu et al., 2021).
- 2 Remote sensing (RS): In this method, water elevation data is collected through altimetry or in-situ measurements, while the surface area of the reservoir is determined using optical satellite imagery. By combining these, an area-elevation curve of the reservoir is generated, which helps calculate the current capacity. The difference between this capacity and the original built capacity indicates the sedimentation volume (Pandey et al., 2016; Zhang et al., 2006).
- 3 Numerical modeling (NM): Sedimentation estimates can also be derived through hydrological and sediment models. These models use in-situ data such as inflow, sediment concentration, and sediment density to simulate sediment transport and deposition in the basin, providing an estimate of sedimentation (Elçi et al., 2009; Hanmaiahgari et al., 2018).

In terms of relative accuracy, the methods for estimating sedimentation rates and reservoir storage vary depending on the approach and data used. Bathymetric surveys are generally considered to provide the most accurate estimates, as they directly measure the reservoir's depth and volume. Satellite remote sensing accuracy is influenced by factors such as image resolution, the method used to estimate the surface area of the reservoir, and whether elevation data is in situ or derived from altimetry. Numerical modeling, on the other hand, depends heavily on the accuracy of input data and the assumptions inherent in the model. While these methods have inherent limitations,

bathymetric surveys typically yield the highest accuracy, followed by remote sensing and numerical modeling, respectively (Nyikadzino & Gwate, 2021; Gao, 2009).

Another attribute incorporated into the GRILSS dataset is the classification of reservoir storage type, indicating whether the sedimentation volume was estimated for live storage or gross storage for each reservoir. Additionally, Google Maps was utilized to verify whether the reservoir had been removed and to determine if it was associated with a creek dam or a dry dam. The website location (i.e., Uniform Resource Locator URL) for each reservoir's original data source was also documented in the dataset. For some reservoirs located in Zambia, the built year was roughly estimated based on sedimentation and capacity loss rates, with these assumptions noted in the comment section.

To ensure compatibility of the GRILSS dataset with one of the most widely used dam datasets, the Global Reservoir and Dam database (GRanD), a comparison was conducted to identify common reservoirs in both datasets (Lehner et al., 2011). This involved creating a 100-meter buffer around the dam locations in the GRILSS dataset. Dams within this buffered radius were then matched to those in the GRanD database.

As a result of the above data curation practices, the GRILSS dataset can now be effectively utilized alongside both the GDAT and GRanD datasets, with increased utility for research and analysis related to reservoir sedimentation, operations and management.

4.3.4. Reservoir polygons

Reservoir sedimentation varies significantly from one reservoir to another, with one key factor being the shape of the reservoir. Generally, sedimentation is higher when the reservoir's shape complexity—defined as the ratio of shoreline length (or wetted perimeter) to surface area—is greater. Conversely, reservoirs with a larger surface area but a lower wetted perimeter, indicating low shape complexity, tend to experience less sedimentation (Kantoush & Schleiss, 2014). Given

the importance of reservoir geometry in sedimentation studies, we undertook efforts to extract the shape polygons for each reservoir in the GRILSS dataset. These shape polygons have the potential to provide valuable insights for future analyses by the global water community.

OpenStreetMap (OSM) was used to extract reservoir geometry shapes for each reservoir based on the dam locations (OpenStreetMap, 2017). The Overpass API was employed to fetch shapes within a 1000-meter radius of each dam. To ensure that only reservoir shapes were selected, the results were filtered based on specific tags such as “natural” = “water,” “water” = “reservoir,” or “water” = “lake” (Overpass, 2024). When multiple shapes were retrieved, the shape closest to the dam's point location was selected.

When applying the initial strategy, no reservoir shapes were found for around 300 reservoirs. Upon closer inspection in QGIS (QGIS, 2024), with OSM as the basemap, it was discovered that for 200 of these reservoirs, the dam coordinates—mostly sourced from GDAT—were significantly misplaced. After manually correcting these coordinates, reservoir shapes were re-extracted from OSM. However, for around 150 reservoirs, the shape remained hard to retrieve.

A quality check was then performed by reviewing each reservoir shape in QGIS using OSM and Google satellite imagery. It was found that for 150 reservoirs, no reservoir polygons existed in OSM, while for 20 reservoirs, the shapes were incomplete, and for 35 reservoirs, the wrong shapes were selected. Each of these cases was manually handled for quality control. For reservoirs with incorrect shapes, the correct OSM IDs were identified using the OSM webapp, and the shapes were re-fetched. For incomplete shapes, multiple OSM shapes were joined to create a single accurate geometry.

For reservoirs without any polygons in OSM, HydroLAKES was used to match dam locations to lake geometries, providing shapes for about 50 reservoirs (Messenger et al., 2016). For the remaining reservoirs, the Global Surface Water Occurrence dataset (Pekel et al., 2016) was used,

but the resulting shapes, derived from raster data, were pixelated. These shapes were manually refined to improve the overall quality of the GRILSS dataset. It is important to note that no reservoir geometry could be derived for dry dams, creek dams, or dams that had already been removed.

4.3.5. Catchment polygons of reservoirs

A major factor that directly impacts reservoir sedimentation is the catchment of the reservoir. Key catchment characteristics such as area, slope, land use, and land cover play a significant role in determining sedimentation rates. To enable users to assess these characteristics, we focused on extracting the catchment polygons for all reservoirs, as these shapes provide valuable insights for sedimentation analysis.

The Watershed (Spatial Analyst) tool in ArcGIS Pro was used to delineate catchments, utilizing a 90 m digital elevation model. To automate this process for over 1000 reservoirs, a geoprocessing workflow was created using Model Builder, a visual programming language. Snap distances were adjusted based on the original built capacity of the reservoirs, with larger reservoirs using larger snap distances (e.g., 1200 meters for those over 1 MCM and 50 meters for those under 0.1 MCM).

However, for a few reservoirs, particularly those in Taiwan, this method was unsuccessful. In those cases, catchment polygons were created using the Python library "pysheds" (Bartos, 2020) and HydroSHEDS flow direction data at 3 arc-seconds resolution (Lehner et al., 2008). Through this combined approach, catchment geometries were successfully obtained for all the reservoirs in the GRILSS dataset, which were then used to calculate catchment area when it was not available from the original source. The catchment shapefiles are provided as supplementary information for users. However, in cases where high-resolution DEMs are required, users are encouraged to use their own catchment geometries to suit the specific needs of their work.

4.4. Dataset Description

The Global Reservoir Inventory of Lost Storage by Sedimentation (GRILSS) dataset contains sedimentation data for over 1000 reservoirs worldwide. Compiling this dataset took sustained effort and methodical work over a year, involving detailed manual corrections, quality assurance, and quality control to ensure its accuracy. To the best of our knowledge, GRILSS is the first dataset of its kind, aimed at supporting global studies on reservoir sedimentation and its impact on water storage. The dataset is composed of four files. The main file, an Excel spreadsheet, contains historical records of reservoir sedimentation, with each record assigned a unique Observation ID (OID). A single reservoir can have multiple records, reflecting sedimentation data over various time periods, and each reservoir is uniquely identified by a Reservoir ID (RID). The remaining three files consist of vector data—available in both shapefile and GeoJSON formats—representing the dam, reservoir, and catchment geometries for each reservoir.

4.4.1. Sedimentation Dataset

The Excel file GRILSS_data.xlsx contains sedimentation data for various reservoirs. The dataset includes 35 fields describing reservoir locations, characteristics, and the sedimentation that occurred over specific time periods. Each record also provides the original source URL, allowing users to explore or learn more about the reservoir or the sedimentation estimation method in detail. Missing values in the dataset are represented by blanks or empty spaces.

One of the fields includes comments that provide additional insights into each record or reservoir, such as its length and the sediment management techniques used. As detailed in Sect. 2.3, the method for estimating sediment volume is specified under the ‘Survey Type’ field and is categorized as ‘BS’ for bathymetric surveys, ‘RS’ for remote sensing, and ‘NM’ for numerical modeling methods. Fields that have been manually corrected, compared to the original source, are noted under the ‘Fields Corrected’ field. Table 4.1 outlines the details of each field in the dataset.

Table 4.1 Overview and Description of Fields in the GRILSS Dataset (Minocha & Hossain, 2025)

S. No.	Field Name	Field Description	Units
1.	GRILSS OID	A unique identifier for each sedimentation record in the dataset	-
2.	GRILSS RID	A unique identifier for each reservoir in the dataset	-
3.	Reservoir	The name of the reservoir	-
4.	Country	The name of the country where the reservoir is located	-
5.	HYBAS_ID	The HydroSHEDS HYBAS_ID for the major basin containing the reservoir	-
6.	Major River Basin	The name of the major river basin, unique to each HYBAS_ID	-
7.	Continent	The continent where the reservoir is situated	-
8.	Capacity Loss Rate (%/year)	Annual rate of reservoir capacity loss, expressed as a percentage of the original built capacity.	%/year
9.	Sedimentation Rate (MCM/year)	Annual rate of sediment deposition in the reservoir	Million cubic meters/year
10.	Capacity Loss (%)	The percentage of the original built capacity (in MCM) that has been lost due to sediment accumulation	Percentage
11.	Sedimentation Amount (MT)	The total amount of sediment deposited in the reservoir	Million tons
12.	Sedimentation Amount (MCM)	The volume of sediment deposited in the reservoir	Million cubic meters
13.	Sediment Bulk Density (ton/m ³)	The estimated bulk density of the sediment deposited in the reservoir	Ton/m ³

14.	Observed Duration (years)	The number of years over which the sedimentation amount was estimated	Years
15.	Observation End Year	The year when the observed duration of sedimentation ended	-
16.	Observation Start Year	The year when the observed duration of sedimentation began	-
17.	Built Year	The year in which the reservoir was constructed	-
18.	Original Built Capacity (MCM)	The reservoir's capacity at the time of construction	Million cubic meters
19.	Catchment Area (km ²)	The area of the reservoir's catchment	Square kilometers
20.	Height (m)	The height of the reservoir's impoundment (dam)	Meters
21.	Latitude	The latitude coordinate of the reservoir's dam	Degrees
22.	Longitude	The longitude coordinate of the reservoir's dam	Degrees
23.	Survey Type	The method used to estimate sedimentation volume in the reservoir [BS, RS, NM]	-
24.	Type of Storage	The type of reservoir storage for which sedimentation volume is estimated [Gross or Live]	-
25.	Comments	Additional information regarding the reservoir or the sedimentation estimation method	-
26.	Original Source URL	The web URL to the original source from which the record was extracted	-
27.	Fields Corrected	Names of fields that were corrected or added after manual inspection for the specific record	-

28.	Fields Computed	Names of fields that were computed for the specific record	-
29.	GDAT Dam Name	The name of the dam associated with the reservoir in the GDAT dataset	-
30.	GDAT Feature_ID	The Feature_ID corresponding to the reservoir in the GDAT dataset	-
31.	GRAND_ID	The GRAND_ID corresponding to the reservoir in the GRanD database	-
32.	GRAND Wrong Location	A binary flag indicating if the dam coordinates are incorrect in the GRanD dataset	-
33.	GDAT Wrong Location	A binary flag indicating if the dam coordinates are incorrect in the GDAT dataset	-
34.	Dam Removed or Dried	A binary flag indicating if the reservoir has been removed or is dried	-
35.	Creek Dam	A binary flag indicating if the dam is classified as a creek dam	-

4.4.2. Vector Dataset

In addition to sedimentation data, the GRILSS dataset also includes associated vector data, as described in Sect. 2. This vector data comprises four files: 1. point locations of the dams associated with the reservoirs, 2. reservoir geometry polygons, 3. catchment geometry polygons, and 4. point locations representing snap points corresponding to dam positions for the creation of catchment boundary polygons. Each vector file contains attributes such as GRILSS RID, Reservoir name, and Country. Notably, the catchment vector file includes computed surface area for the reservoir catchments, which may differ from the catchment area reported in the sedimentation data derived from the original source.

4.5. GRILSS Dataset

4.5.1. Overview

The GRILSS dataset contains 1368 records for 1013 reservoirs worldwide. These reservoirs span 75 major river basins and 54 countries, representing a wide range of catchment types with varying physical characteristics such as slope, climate, land use, land cover and soil type. Figure 4.1 highlights the 15 countries and major river basins with the highest number of reservoirs. The dataset also covers a wide range of dam construction periods, with few reservoirs dating back to the 1700s and 1800s. Most reservoirs, however, were constructed between 1950 and 2000, as shown in Figure 4.2(b). The oldest reservoir in the dataset, Pareton in Spain, was built in 1713 (Erena et al., 2019) and has a capacity loss rate of 0.3% per year.

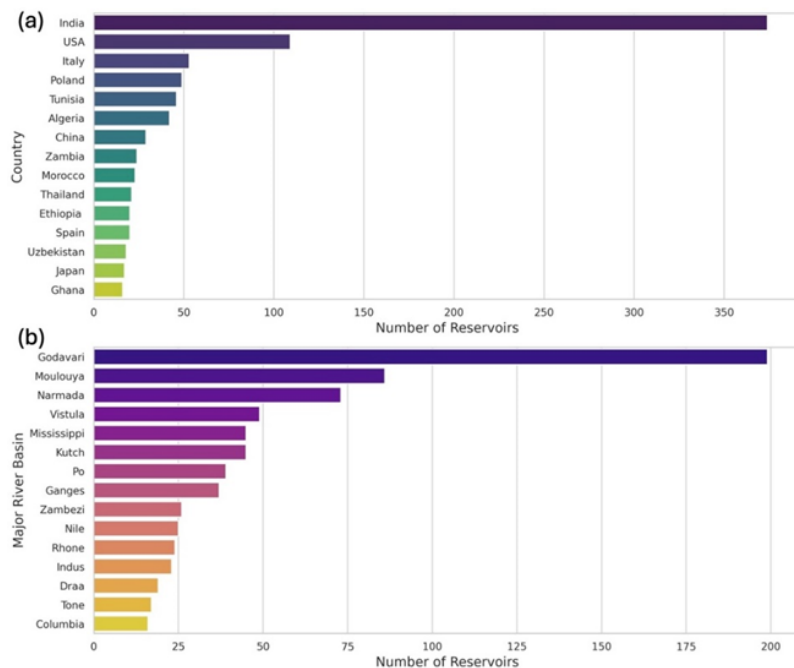


Figure 4.1 The top fifteen (a) countries and (b) major river basins having the highest number of reservoirs in the GRILSS dataset.

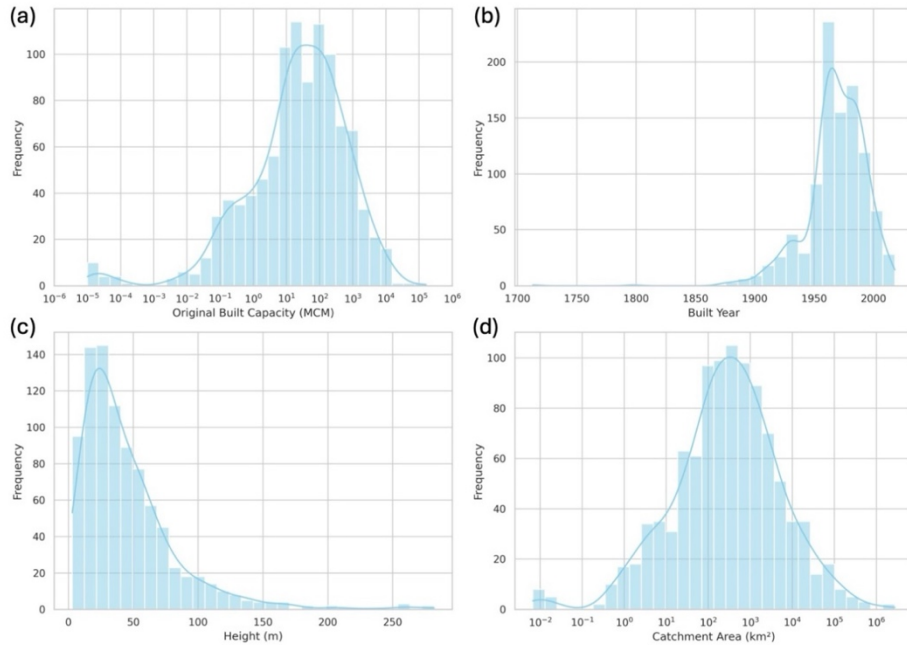


Figure 4.2 Frequency distribution of reservoir attributes: (a) original built capacity, (b) construction year of dams, (c) dam height, and (d) catchment area. Each panel shows the distribution of these characteristics across the reservoirs in the dataset, with the blue line representing the kernel density estimate (KDE) of the distribution.

In terms of survey methods, the dataset includes 1182 records based on bathymetric surveys (BS), 175 from remote sensing (RS), and 11 from numerical modeling (NM). The dataset also captures considerable variation in terms of the original built capacity of reservoirs, though reservoirs with capacities below 0.1 MCM are underrepresented (Figure 4.2(a)). It includes 21 creek reservoirs, small dams constructed across creeks, all located in the United States. The smallest reservoir, a creek sediment dam, has an original built capacity of just 9.9 m³. Additionally, 13 reservoirs in the dataset, all in the U.S., have either been removed or are part of dry dams. The largest reservoir in the GRILSS dataset is Lake Nasser in Egypt, with an original built capacity of 162 km³. Lake Nasser has one of the lowest capacity loss rates in the dataset, at 2.3×10^{-4} % per year.

The height of the dam is available for only 883 reservoirs in the dataset, collected from various sources as it was not consistently provided in the original data source. Figure 4.2(c) displays the frequency distribution of dam heights, with most dams being under 75 meters tall. The average

height in the dataset is 45.58 meters. Cerro Prieto in Mexico, the tallest dam in the GRILSS dataset, stands at 282 meters with a capacity loss rate of 0.31% per year. In terms of catchment area, the dataset includes reservoirs with catchment sizes ranging from less than 1 km² to over 0.1 million km². The distribution of catchment areas follows a normal pattern, with a mean of 14,759 km² (Figure 4.2(d)).

4.5.2. Capacity loss rate

The capacity loss rate was first averaged across all records for each reservoir. From these reservoir-specific averages, the overall mean annual capacity loss rate for all reservoirs was determined to be 1.62% per year. Mayfair Lake in the USA had the highest observed loss rate at 102.24% per year. Some reservoirs even reported negative capacity loss rates due to sediment management practices like dredging (Central Water Commission, 2020). Figure 4.3 shows the distribution of dams in GRILSS dataset and provides an overview of the rates at which reservoirs are losing capacity across different regions of the world. Figure 4.4(a) presents a histogram of the capacity loss rates, showing that the majority of reservoirs, 745 in total, have a loss rate of less than 1% per year.

4.5.2.1. Capacity loss rate by built capacity

Of the 1013 reservoirs, 174 (17.18%) have an initial built capacity of less than 1 million cubic meters (MCM), exhibiting an average capacity loss rate of 5.4% per year. This higher rate is largely attributed to creek dams, which can experience capacity loss rates as high as 132% per year due to their small size and short observed durations (around 1 year). The remaining 82.82% of reservoirs, with an initial capacity of 1 MCM or more, have an average capacity loss rate of 0.84% per year, consistent with global sedimentation rates reported by Basson (2009). Figure 4.4(b) shows the distribution of capacity loss rates for small (<1 MCM) and large reservoirs (≥1 MCM), while Table 4.2 summarizes these statistics for the GRILSS dataset.

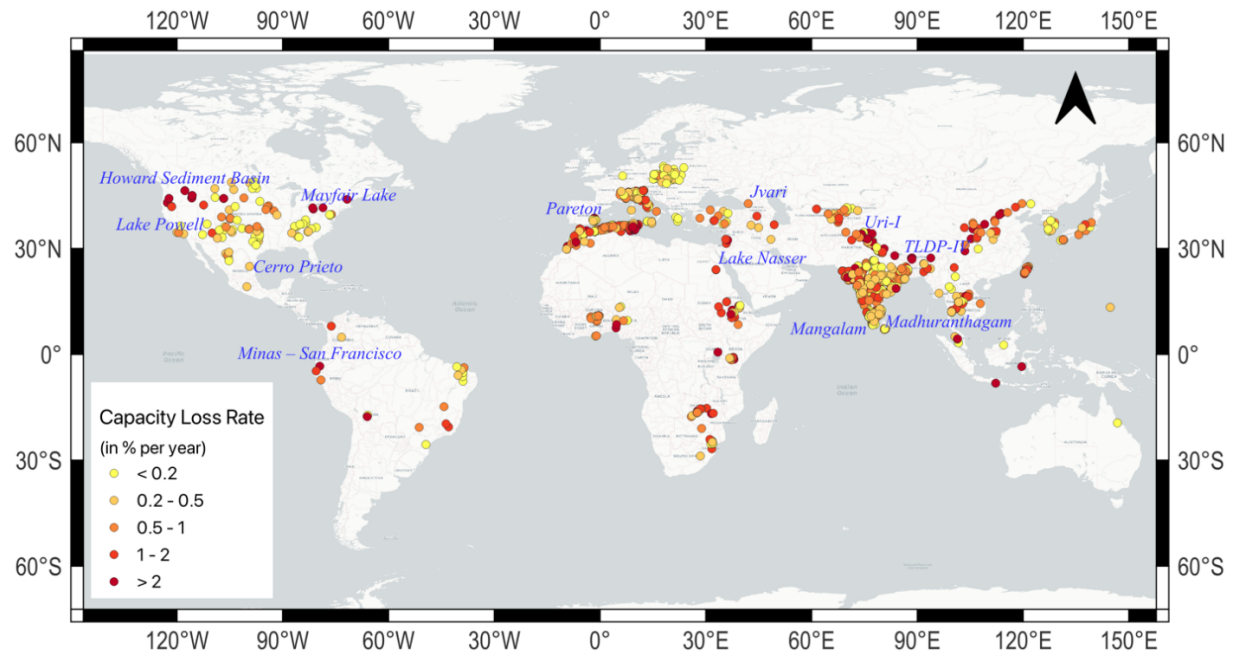


Figure 4.3 Map displaying the locations of all reservoirs in the GRILSS dataset. Marker colors represent the capacity loss rate (% per year), with darker shades indicating higher loss rates. Names of select reservoirs referred to in the text or other figures are also labelled for additional information.

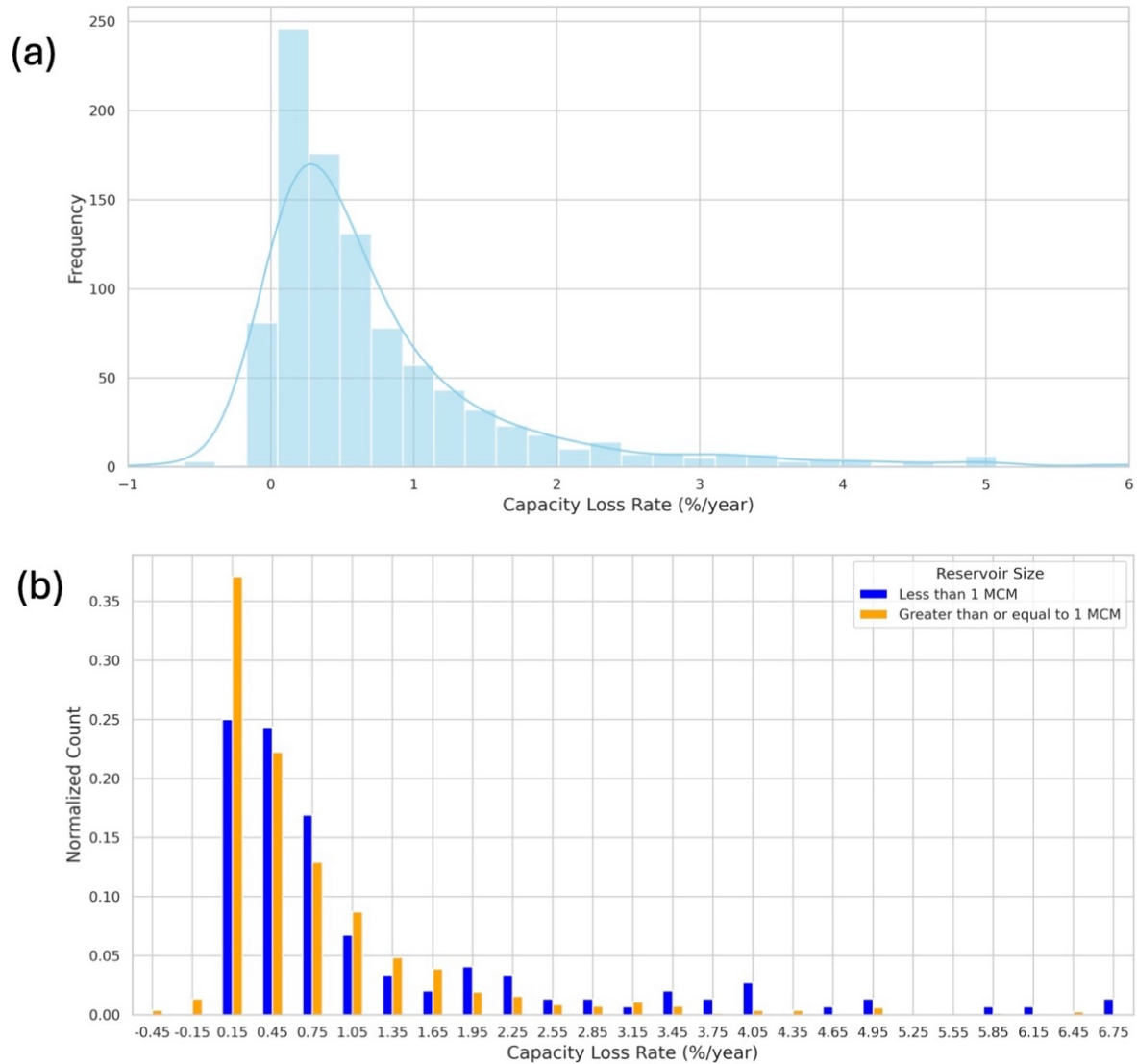


Figure 4.4 (a) Frequency distribution of capacity loss rates for all reservoirs, with the blue line representing the kernel density estimate (KDE). (b) Distribution of capacity loss rates for reservoirs with an original built capacity of less than 1 MCM compared to those with a capacity of 1 MCM or more, normalized by the total count in each category.

Table 4.2 Statistics of annual capacity loss rate expressed as percentage of initial capacity of the reservoir (% a-1)

	Number of reservoirs	Min	Average	Median	Capacity- weighted mean	Max
Capacity <1 MCM	174	0.0	5.4	0.76	1.2	102.24
Capacity >1 MCM	839	-1.91	0.84	0.41	0.42	21.03

4.5.2.2. Capacity loss rate by observed duration

The observed duration for each record represents the time period over which sedimentation rates were estimated. Similar to the capacity loss rate, this duration was averaged across all records for a reservoir. As described in Section 4.3.1, if only the capacity loss rate or sedimentation rate was provided without specific duration information, it was assumed to be one year.

Figure 4.5(a) illustrates that the capacity loss rate decreases as the observed duration increases. Additionally, for shorter observed durations, smaller reservoirs tend to exhibit higher capacity loss rates, while larger reservoirs show lower rates. This relationship between observed duration and capacity loss rate may result from variable sedimentation rates over time. Sedimentation rates are typically higher during significant storm events and floods; thus, a shorter observed duration is more likely to encompass a substantial portion of these events, leading to increased capacity loss rates.

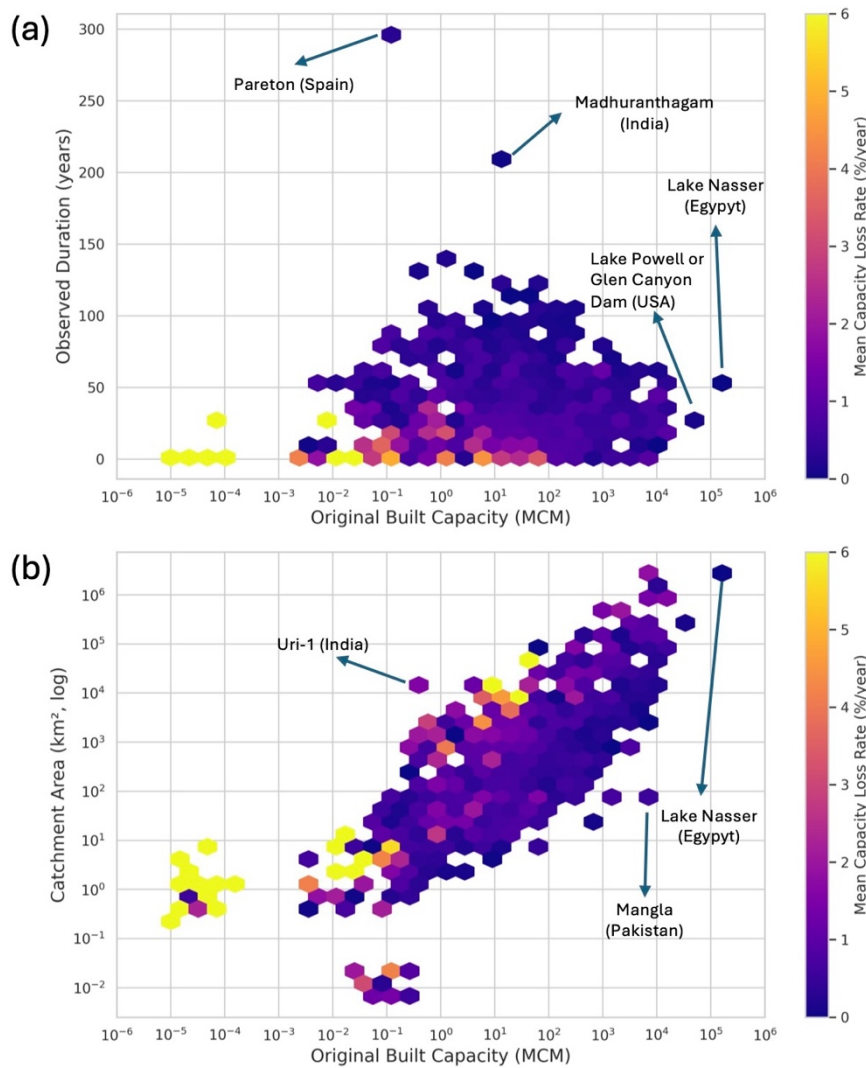


Figure 4.5 Density scatter plot showing hexagonal bins corresponding to specific (a) built capacity and observed duration, and (b) original built capacity and catchment area of the reservoirs. The color gradient represents the mean capacity loss rate for all reservoirs within each hexagonal bin in both panels. Name of the reservoir, along with the country is mentioned for few outliers, where there was only one reservoir in the bin.

4.5.2.3. Capacity loss rate by catchment area

Larger reservoirs tend to have larger catchment areas, while smaller reservoirs typically have smaller catchment areas, as illustrated in Figure 4.5(b). A similar relationship was observed by

Walter et al. (2020) between catchment area and the reservoirs in terms of surface area. This figure also reinforces earlier observation that smaller reservoirs experience higher capacity loss rates. Notably, for a given built capacity, the capacity loss rate increases with the catchment area. This trend may be attributed to a greater availability of soil for erosion in large catchment areas.

4.5.2.4. Capacity loss rate by height

Figure 4.6 indicates that dam height does not significantly influence the capacity loss rate. However, it is observed that beyond a certain height—approximately 90 meters—the loss rate tends to remain low and does not reach high values. This pattern may again be attributed to larger capacity dams, which are generally taller and, consequently, exhibit lower loss rates.

4.5.2.5. Capacity loss rate by built year

The GRILSS dataset includes two dams constructed in the 1700s, a few built in the 1800s, and many that extend into the twentieth and twenty-first centuries. This diverse range of construction years allows for an exploration of the relationship between the year a dam was built and its capacity loss rate. Figure 4.7 displays the median capacity loss rate for each year of construction, revealing an intriguing trend: reservoirs built more recently tend to have slightly higher capacity loss rates compared to older reservoirs. This subtle upward trend suggests that newly constructed reservoirs may be losing capacity at an accelerated rate.

One possible explanation for this phenomenon is that sediment removal efforts are primarily focused on older reservoirs, while relatively newer ones have received less attention. Additionally, this long-term trend may be influenced by factors such as climate change and urbanization, and therefore needs to be further investigated.

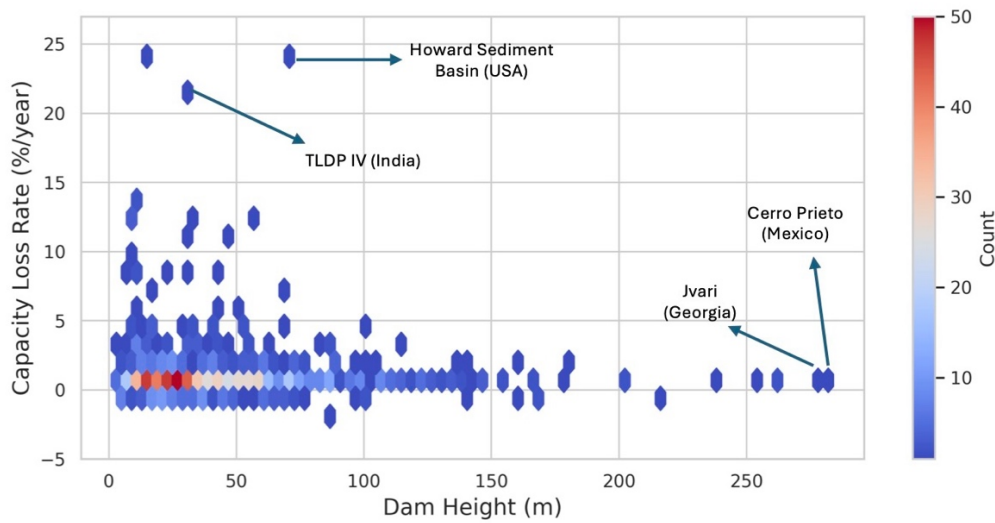


Figure 4.6 Density scatter plot depicting the relationship between dam height (in meters) and capacity loss rate (% per year) within each hexagonal bin. The color gradient indicates the number of reservoirs contained in each bin. Name of the reservoir, along with the country is mentioned for few outliers, where there was only one reservoir in the bin.

4.5.2.6. Capacity loss rate by Country

Total reservoir storage capacity is a critical concern for all countries as it determines the available freshwater for irrigation, domestic, and industrial use. To manage water resources effectively, it is essential for water managers to understand the average capacity loss rate within their country. Figure 4.8 presents the median capacity loss rates for 54 countries represented in the GRILSS dataset. Lighter shades, such as peach and light pink, indicate lower capacity loss rates (0–0.8% per year), while darker shades highlight countries experiencing higher losses (up to 7% per year). Countries where fewer than three reservoirs are available in the GRILSS dataset are outlined in red, marking the data for these areas as lower confidence. Notably, the United States and several countries in Southeast Asia show significantly higher capacity loss rates, indicating increased sedimentation challenges in these regions. This observation overall aligns with the findings of Perera et al. (2023), who also reported the highest capacity losses in the United States.

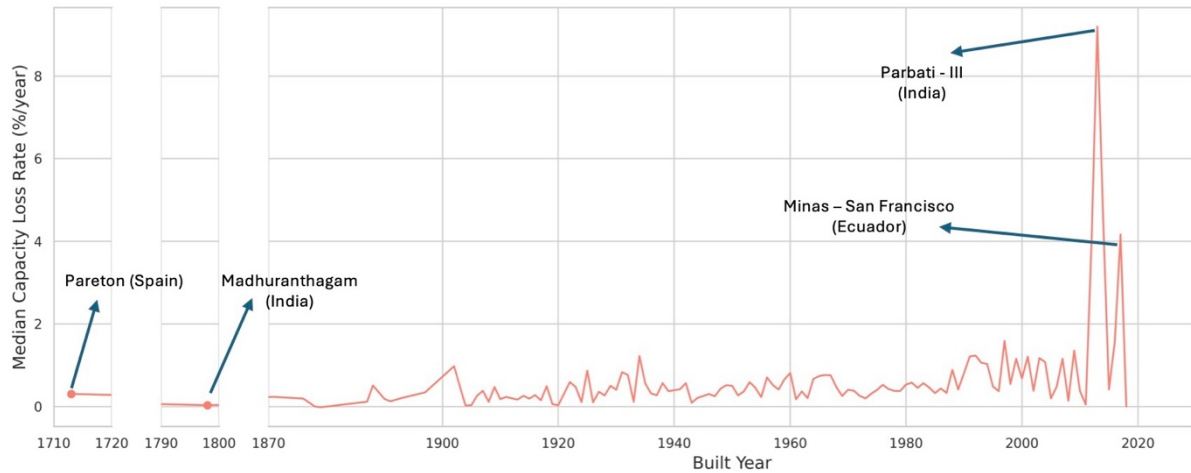


Figure 4.7 Median capacity loss rate for each year of construction among the GRILSS reservoirs. The x-axis shows two distinct kinks corresponding to the two reservoirs built in the 18th century. Reservoir names are indicated for those constructed in that century and for any that exhibit anomalously high capacity loss rates relative to the overall trend.

4.5.3. Sedimentation rate

While capacity loss rates are crucial for countries and water managers, understanding sedimentation rates is equally important, as they indicate which regions are experiencing more intense sedimentation. As discussed in Section 4.2, factors such as a region's topography and climate play a key role in influencing sedimentation. For each reservoir, the sedimentation rate was averaged across all records. Figure 4.9 presents the distribution of sedimentation rates across the GRILSS dataset. Notably, 17 reservoirs reported negative sedimentation rates, likely due to sediment removal efforts. The median sedimentation rate in the dataset is 0.14 MCM per year, while the mean rate is significantly higher at 2.79 MCM per year. This difference is due to a few reservoirs with exceptionally high sedimentation rates, such as Xiaolangdi and Sanmenxia in the Yellow River basin, where rates reach around 200 MCM per year. In total, 60 reservoirs report sedimentation rates exceeding 10 MCM per year.

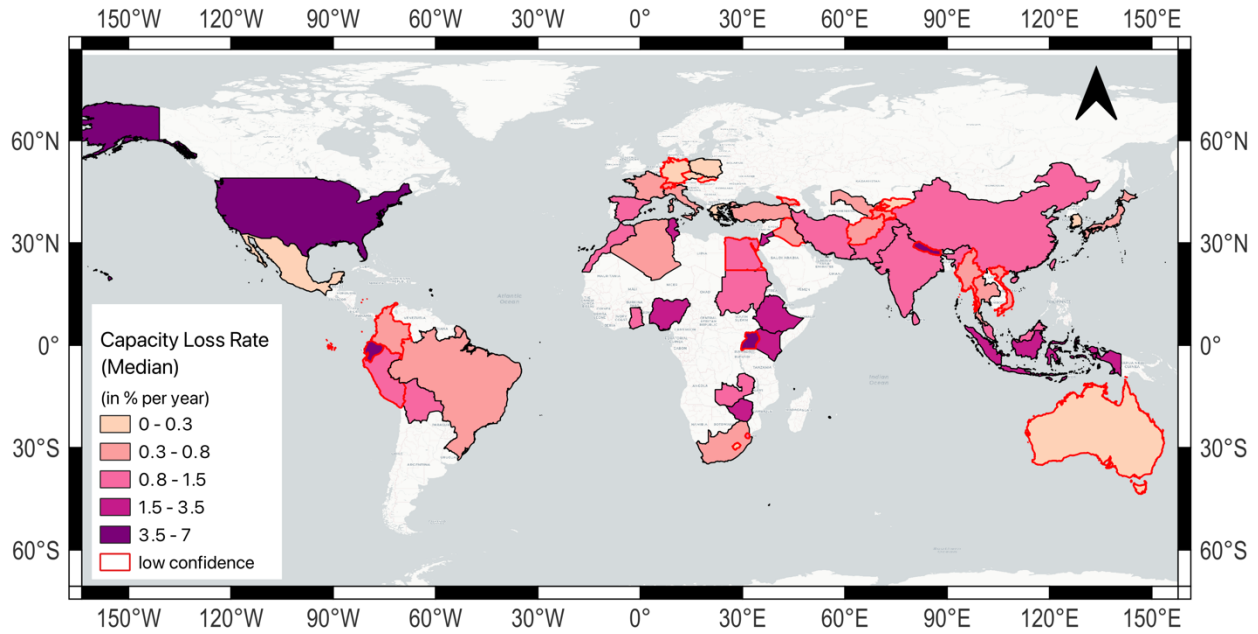


Figure 4.8 World map displaying the 54 countries covered by reservoirs in the GRILSS dataset. The color fill indicates the median capacity loss rate (% per year) for each country. Countries with fewer than three reservoirs are outlined in red, signifying lower confidence in the estimated loss rate for those regions.

4.5.3.1. Sedimentation rate by river basins

The 1013 reservoirs in the GRILSS dataset are distributed across 75 major river basins worldwide, each characterized by varying geography, climate, vegetation, population density, and topography.

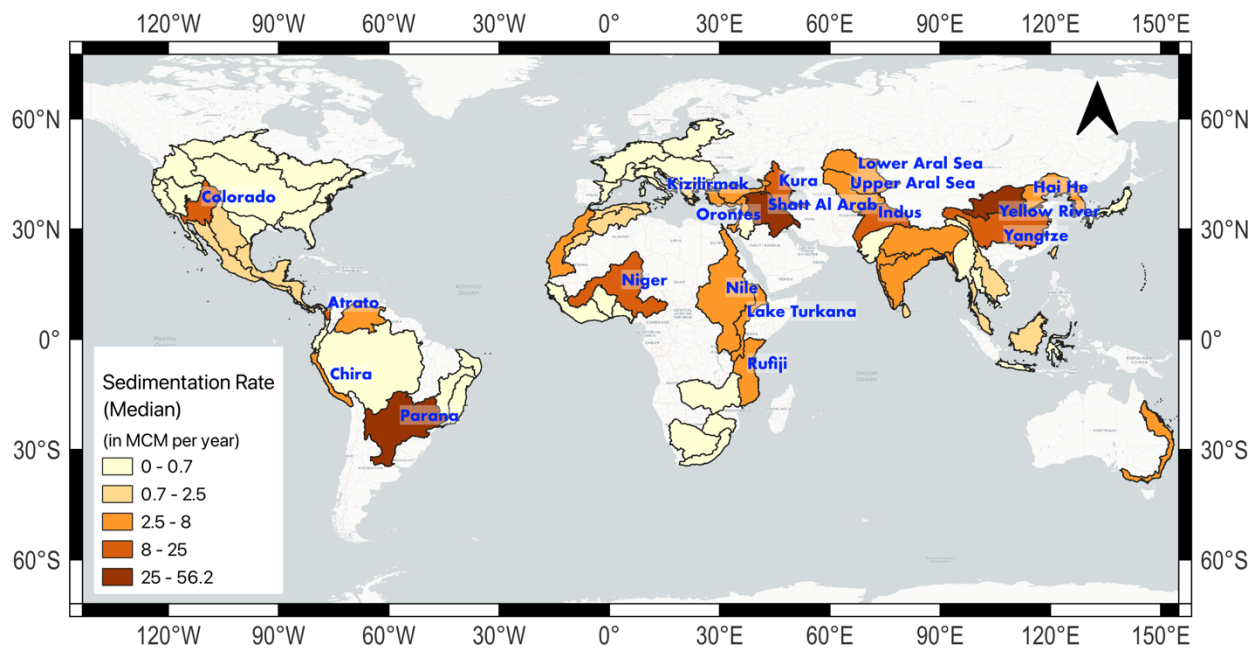


Figure 4.10 illustrates the median capacity loss rates for these river basins, with lighter shades of yellow representing lower sedimentation rates (0-4 MCM per year) and darker brown shades indicating higher rates (up to 56 MCM per year). The Parana River basin in South America exhibits the highest sedimentation rate at 56.2 MCM per year, followed by the Yellow River basin at 31.4 MCM per year. All river basins with sedimentation rates exceeding 8 MCM per year are labeled on the map. River basins in North America and Europe exhibit lower sedimentation rates, whereas those in Asia and Africa tend to have higher rates.

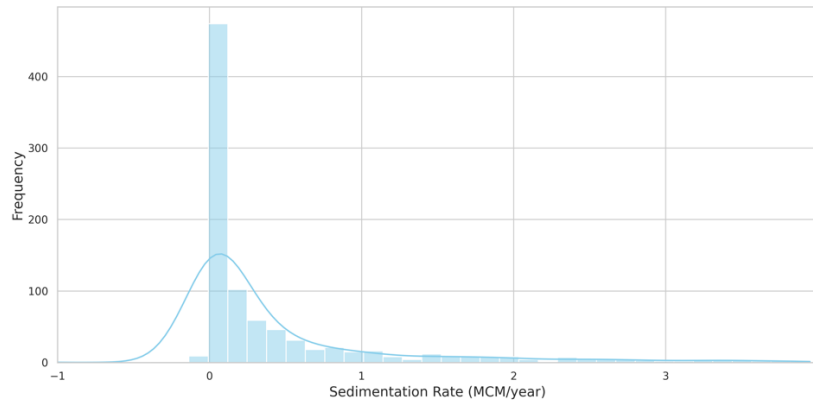


Figure 4.9 Frequency distribution plot of sedimentation rates (in MCM per year) for reservoirs in the GRILSS dataset, with a blue line representing the kernel density estimate.

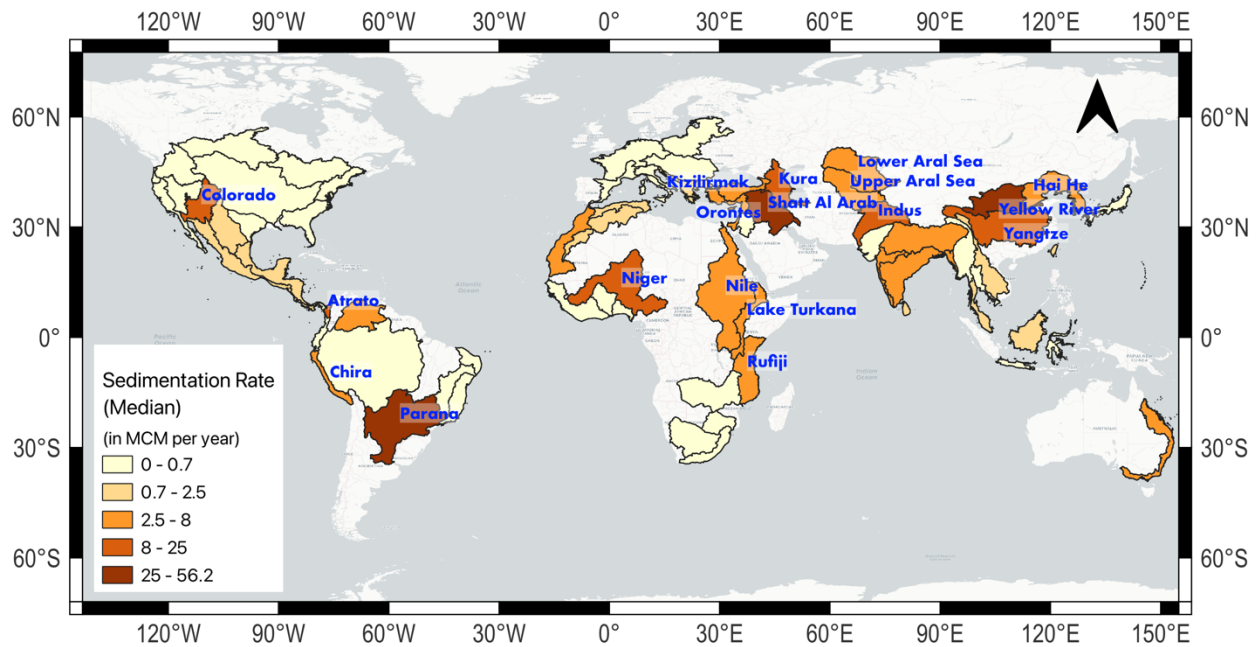


Figure 4.10 Map depicting the median sedimentation rates of reservoirs across 75 major river basins represented in the GRILSS dataset. River basins with sedimentation rates of 8 MCM or more are labeled on the map.

4.6. Discussion and Conclusion

Reservoirs play a critical role in meeting global freshwater demands for agriculture, domestic use, energy production, and industrial purposes by storing and regulating water supplies. Despite the continued construction of many new reservoirs worldwide, the total global storage capacity is in decline due to sedimentation. This loss of capacity is a growing concern, as sedimentation rates vary widely depending on factors such as the reservoir's location, catchment area, climate, topography, and soil characteristics. As a result, understanding the complexities of reservoir sedimentation requires localized studies that account for these unique environmental conditions.

While numerous studies have estimated sedimentation rates for individual reservoirs or small regions, these efforts have largely remained fragmented, having disparate curation and confined to local scales. One notable global study by Wisser et al. (2013) attempted to estimate global storage capacity loss using observed reservoir sedimentation rates. However, due to the lack of open-source data and the skewness of data toward reservoirs located in the United States (with over 1,000 records from the US and only 191 from the rest of the world), similar or follow up studies may have not been scalable. Thus, a lack of an organized, open-source dataset with a consistent curation practice that captures the reservoir sedimentation problem on a global scale, has limited the global use of sedimentation data.

Global dam datasets, such as GRanD (Lehner et al., 2011) and GDAT (Zhang & Gu, 2023), often include detailed reservoir attributes but generally lack sedimentation data. Similarly, data from the International Commission on Large Dams (ICOLD, 2019), while extensive, are not freely accessible in a readily usable tabular format. National-level efforts to compile reservoir sedimentation data, such as those for the United States (Gray et al., 2010), India (Central Water Commission, 2020), South Africa (Masadala et al., 2010), and Italy (Patro et al., 2022), have served as a valuable resource. However, these datasets lack standardized curation protocols and are often inconsistent in the metrics they report. At the continental scale, Vanmaercke et al. (2014) compiled sediment yield data for 682 African catchments based on 84 publications and reports. While this work represents a significant contribution, it does not provide specific information on reservoir capacity loss.

To the best of our knowledge, GRILSS is the first comprehensive dataset to be able to track and compare sedimentation rates across reservoirs worldwide. GRILSS also enables the analysis of temporal variations in sedimentation rates driven by changes in hydrological conditions—an aspect not captured by earlier datasets. With 1013 reservoirs spanning 75 major river basins and 54 countries, GRILSS provides critical insights into the extent of the problem worldwide. Compiled from 143 diverse and traceable sources, including published articles, government documents, and online databases, this dataset is a crucial resource for the global water community.

In an era where data and open access are essential, GRILSS opens new avenues for data-driven freshwater management on a global scale. Beyond sedimentation rates, the dataset also includes key reservoir attributes such as built capacity, dam height, and catchment area, along with information on the methods used to estimate sedimentation and the time period of observations. Additionally, GRILSS provides vector data on reservoir geometries and catchments, making it a versatile tool for researchers and policymakers alike.

Initial analysis of the GRILSS dataset suggests a concerning trend of higher capacity loss rates in more recently constructed reservoirs, indicating that newer infrastructure may be more vulnerable to sedimentation and reservoir operation efficiency. Additionally, we observed significant regional differences in sedimentation rates, with river basins such as the Parana and Yellow River experiencing some of the highest sedimentation rates globally. These insights underscore the need for targeted, region-specific sediment management strategies. It is important to note that this preliminary analysis primarily aims to highlight the strengths and potential of the GRILSS dataset, offering initial insights into sedimentation trends rather than providing a comprehensive critical appraisal of global sedimentation patterns.

While the dataset provides valuable insights into reservoir sedimentation, certain limitations must be acknowledged. The underrepresentation of smaller reservoirs (<0.1 MCM) may bias global

capacity loss rate estimates, as smaller reservoirs typically exhibit higher loss rates relative to their total storage capacity. Geographical coverage is also uneven, partly due to reliance on English-language publications, which could overrepresent regions with better documentation. GDAT was used for georeferencing reservoirs, and dam coordinates were manually reviewed to ensure accuracy. However, parameters like original built capacity and dam height, wherever missing, were also derived from GDAT. Since GDAT often lacks complete records for smaller dams, particularly in developing regions, it can introduce potential biases. These limitations emphasize the need for future efforts to include multilingual publications, validate data from multiple sources, and conduct more surveys for smaller reservoirs to achieve a more accurate representation of global reservoirs.

By organizing data on sedimentation and capacity loss that is also compatible with widely used existing reservoir datasets, GRILSS provides water managers, policymakers, and researchers a powerful dataset for planning and implementing better reservoir management practices. As the first dataset of its kind, GRILSS provides a foundation for future research into the myriad factors influencing reservoir sedimentation, including climate change, land use, and sediment management practices. Its global scope opens the gateway for collaborative data curation on reservoir sedimentation, enabling the community to bridge existing gaps to sustain a growing dataset for large-scale, global studies on reservoir sedimentation (Minocha & Hossain, 2025).

A dataset of observed sedimentation records, however, is most valuable when it can be extended beyond the reservoirs it directly documents. The overwhelming majority of the world's reservoirs have no bathymetric survey on record, and data-sparse regions are precisely the ones where management decisions are most consequential. What is needed is a predictive model—one trained on the physical, climatic, and operational features that GRILSS reveals as the dominant drivers of sedimentation—that can produce reliable estimates for reservoirs where no in-situ measurements exist. Chapter 5 introduces RECLAIM (Reservoir Estimation of Capacity Loss using AI based Methods), a globally scalable machine learning framework that uses satellite-derived observations and catchment characteristics to predict sedimentation rates, transforming the observational foundation of GRILSS into an operational screening tool for the global water community.

Chapter 5. RECLAIM: A Globally Scalable Machine Learning Framework to Predict Reservoir Sedimentation and Capacity Loss from Satellite-based Earth Observations

Note: This chapter has been published in its current form in *Environmental and Modeling Software*. The only differences are in the numbering of figures, tables, and references to other sections. [Publication: Minocha, S., Hossain, F., Zhao, J., & Istanbuluoglu, E. (2026). RECLAIM: A globally scalable machine learning framework to predict reservoir sedimentation and capacity loss from satellite-based earth observations. *Environmental Modelling & Software*, 204, 107055. <https://doi.org/10.1016/j.envsoft.2026.107055>]

5.1. Abstract

Most reservoirs remain poorly sampled of their actual capacity due to the high costs and logistical demands of conventional sedimentation surveys. Here, we present RECLAIM (**R**eservoir **E**stimation of **C**apacity **L**oss using **AI**-based **M**ethods), a globally scalable framework to predict absolute sedimentation rates using observed records and multi-decadal Earth observations from satellite data (1984-2023). Using a dataset of 1,315 reservoirs with 88 static and dynamic catchment, climatic, and reservoir-specific features, RECLAIM integrates gradient boosting models in a dynamic ensemble, achieving a prediction RMSE of 4.44 Million Cubic Meter (MCM)/year, Mean Absolute Error (MAE) of 1.65 MCM/year, and R^2 of 0.86 on the fixed test set. Cross-validation across 10 data partitions yields $RMSE = 7.62 \pm 4.86$ MCM/year and $MAE = 3.13 \pm 1.66$ MCM/year, confirming stable generalization across diverse sedimentation regimes. The development of RECLAIM revealed that absolute sedimentation rate is a more robust predictand than the widely used capacity loss rate, which loses sedimentation physics when normalized by reservoir capacity. The use of RECLAIM is expected to support the long-term sustainability of reservoir infrastructure globally.

5.2. Introduction

Dams and reservoirs play a crucial role in modern society, providing freshwater for domestic consumption, agriculture, and industry, generating hydropower, and offering flood protection. However, these benefits come with substantial ecological and hydrological trade-offs (Bergkamp

et al., 2000; Mulatu et al., 2012). Hereafter, we use the terms dam and reservoir interchangeably to refer to the coupled dam–reservoir system. One of the critical environmental challenges posed by reservoirs is the interruption of sediment transport. As rivers carry sediment downstream, reservoirs act as barriers, trapping this material and preventing it from reaching natural floodplains, deltas, and coastal environments (Schleiss et al., 2016). This process, known as reservoir sedimentation, leads to a gradual reduction in storage capacity and threatens the long-term sustainability of these water infrastructures (Kondolf et al., 2014 and Wisser et al., 2013). Reservoir sedimentation, when quantified from observations, provides opportunities to investigate sediment yields from upslope catchments.

The global significance of this issue has become increasingly clear. Estimates suggest that total global reservoir capacity likely peaked in 2006 and has since entered a phase of decline or has just flattened (Wisser et al., 2013; Perera et al., 2022). Between 1987 and 2010, global per capita reservoir capacity decreased by 19%, and when estimated sedimentation is considered, this decline rises to 21%. These figures highlight that storage loss is not a localized or isolated problem but a process that has already begun to undermine global water security.

Unlike the physical structure of dams, which may deteriorate gradually over many decades, sedimentation can erode reservoir capacity at much faster rates, effectively determining the operational lifespan of many reservoirs (Morris & Fan, 1998). In addition to diminishing water supply, sediment accumulation can obstruct intakes and turbines, reduce hydropower efficiency, increase flood risks, and disrupt the transport of sediment essential to downstream floodplains and coastal systems (Grant et al., 2005; Alam, 1999; Brandt, 2000; Adamo et al., 2021; Petts & Gurnell, 2005). Given these impacts, accurately assessing reservoir sedimentation rates is crucial for long-term water resource management and infrastructure safety (Schleiss et al., 2016, George et al., 2017).

Sedimentation rates are highly variable and shaped by a complex set of watershed, hydro-climatic, and physical design factors. Catchment slope, land use, inflow regimes, precipitation patterns, river

and reservoir morphology, and operational practices can all contribute to how quickly capacity is lost (Obialor et al., 2019; Bui et al., 2023; Kidane & Alemu, 2015). This intricate combination of diverse and dynamic factors makes understanding and estimating reservoir sedimentation rates particularly challenging (Schmitt & Minderhoud, 2023, Schleiss et al., 2016). Thus, the main methods currently available to measure sedimentation reflect these challenges (summarized next).

Direct approaches, such as bathymetric surveys or sediment core sampling, provide accurate estimates but are costly, labor-intensive, and difficult to scale and repeat frequently across large number of sites (Furnans & Austin, 2008; Beckers et al., 2018). Indirect approaches, including modeling and remote sensing–based bathymetry, are less resource-intensive but depend on detailed local data, extensive field campaigns, or assumptions that are not always met (Goel et al., 2002; Ching-Hsien et al., 2012; Foteh et al., 2018). Consequently, most reservoirs around the world remain poorly sampled or estimated of its sedimentation, and dam managers often lack the information needed to prioritize interventions.

This current situation highlights a clear gap in current sedimentation management practice for reservoirs. With thousands of reservoirs worldwide and sedimentation steadily eroding their storage capacity, there is a need for approaches that are efficient, cost-effective and scalable. Reliable, low-cost methods are essential not only to identify which reservoirs are potentially most affected, but also to understand the watershed, hydrological, and design factors driving capacity loss. Indirect, data-driven (machine-learning) approaches that leverage Earth observations from satellites offer a promising way forward.

However, for decades, the development of scalable methods for reservoir sedimentation has been constrained by the absence of a unified, open-source global dataset (Syvitski et al., 2003; Wisser et al., 2013; Perera et al., 2023). As a result, most machine learning approaches have remained highly localized, typically focusing on a small number of reservoirs within individual regions (Lukas et al., 2024; Tan et al., 2025).

This limitation stems from two key challenges: the lack of cross-regional feature diversity, which restricts model generalization across varying hydro-climatic and geomorphological settings, and the limited integration of multi-source data, particularly the combination of in-situ sedimentation observations with multi-decadal satellite-derived variables (Cox et al., 2024; Giri et al., 2021; Garg and Jothiprakash, 2013). Consequently, the potential of Earth observations for scalable sedimentation prediction has remained largely underutilized.

The recent development of the Global Reservoir Inventory of Lost Storage by Sedimentation (GRILSS) addresses a key part of this challenge by providing a globally curated set of observed sedimentation records for 1,013 reservoirs (Minocha and Hossain, 2025a). Figure 5.1 illustrates the geospatial distribution of these reservoirs along with their capacity loss rates. When combined with multi-decadal satellite Earth observations, such a dataset creates a unique opportunity to overcome both limitations—enabling models to leverage diverse, globally distributed features while integrating multi-source observational and satellite-derived data.

In this study, we introduce **RECLAIM** (**R**eservoir **E**stimation of **C**apacity **L**oss using **AI**-based **M**ethods), a data-driven framework that integrates in-situ information, satellite remote sensing, and machine learning to estimate reservoir capacity loss. The objectives of this work are threefold: first, to develop and test RECLAIM as an indirect method for estimating reservoir sedimentation using both quantitative (absolute) and qualitative approaches (relative); second, to assess which data-driven approaches provides more reliable screening of reservoir capacity loss; and third, to investigate from a data-driven perspective the relative importance of geophysical features that influence sedimentation rates. RECLAIM is designed in principle to augment the effective use of expensive hydrographic surveys, and not replace them, by providing a scalable first-level assessment that can optimize limited monitoring and management resources later.

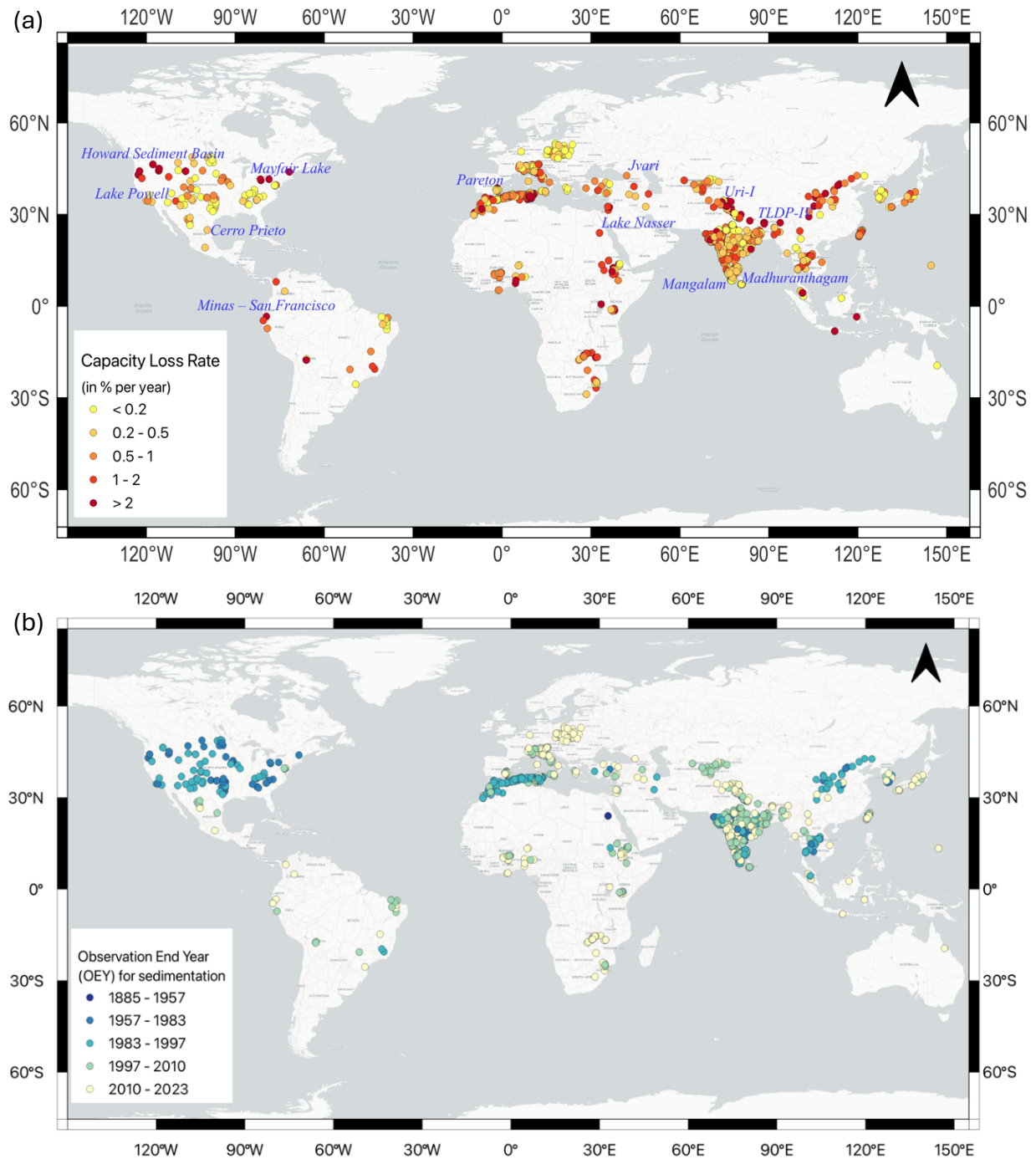


Figure 5.1 Geospatial distribution of 1,013 reservoirs included in the GRILSS (Global Reservoir Inventory of Lost Storage by Sedimentation) dataset (after Minocha and Hossain, 2025a). (a) Colors represent observed capacity loss rates, with labels highlighting selected major reservoirs. (b) Colors denote the most recent end year of sedimentation observational records (OEY, Table 5.2).

5.3. Feature Complexity vs. Global Scalability of RECLAIM

Reservoir sedimentation is a complex and spatially diverse process influenced by numerous hydrological, geomorphological, and operational factors (Schleiss et al., 2016; Obialor et al., 2019). Simple models with only a few variables have generally failed to provide reliable predictions at large scales (Minear and Kondolf, 2009; Almubaidin et al., 2023). To capture this complexity, RECLAIM is designed to leverage a comprehensive set of 88 predictor variables, including static catchment and reservoir attributes as well as satellite-derived dynamic features. This key design philosophy ensures that the model captures the key drivers of sedimentation while maintaining predictive skill across diverse reservoirs worldwide.

Despite the extensive feature set, RECLAIM is designed for scalability and ease of use. Its choice of machine learning algorithms (gradient boosting methods) are driven by the need to handle missing values and an ability to generate reliable predictions even when only a subset of features is available (Al-Sarem et al., 2020; Feng et al., 2025). Feature engineering and transformations are performed automatically within the framework. Users can provide reservoir or catchment polygons for RECLAIM to extract spatial features such as land cover, land use, and geometric metrics. This flexibility allows the RECLAIM tool to be applied globally without exhaustive data collection, balancing the necessary complexity for skillful predictions with global scalability and practical usability at the reservoir scale.

To provide ease of usability, RECLAIM is implemented as an open-source Python package, **pyreclaim** (available at <https://pypi.org/project/pyreclaim/>). The package allows users to run the trained model locally or integrate it into their own workflows. Input data are provided in the form of a Pandas DataFrame with column headers matching the abbreviations of the 88 predictor variables. The framework automatically handles feature preprocessing and missing values, and predictions can be generated as continuous sedimentation rates. Comprehensive documentation and user guides are available at <https://reclaimio.readthedocs.io/en/latest/>, where users can find instructions on loading the pretrained model, adding new reservoirs, and retraining with additional data if desired.

5.4. Data

Over 10 global temporal data products and 5 static specialized datasets were processed, resulting in 88 variables that capture various dimensions of the reservoir sedimentation process. These variables span reservoir design attributes, catchment characteristics, hydrological conditions, and climatic drivers.

For clarity, the data are described here into two parts. First, we describe the observed sedimentation rates, which serve as the target variable (predictand) for training and evaluating RECLAIM (Section 5.4.1). Next, we present the predictor variables, grouped into two categories: static features, representing long-term physical and design attributes of reservoirs and their catchments (Section 5.4.2), and dynamic features, representing temporal variability in hydrological and climatic conditions (Section 5.4.3).

To facilitate tracking and referencing of the variables, each feature is assigned a unique ID: predictors are labeled “P” (e.g., P1, P2), target variables “T”, and all other features not used directly in the RECLAIM model are labeled “D” as they have been used solely to derive other predictors. For example, D3 refers to the end year of the observation; while not itself a predictor, it was used to calculate the dam’s age at the end of the observation period, which became predictor P73. Each feature also has a concise abbreviation for ease of readability and analysis that is used in tables, figures, and text.

5.4.1. Sedimentation Data

Observed data are essential for training and evaluating any data-driven model. For this study, we used the Global Reservoir Inventory of Lost Storage by Sedimentation (GRILSS), a dataset that reports more than 1300 sedimentation (or capacity loss) observations from 1,013 reservoirs worldwide (Minocha and Hossain, 2025b). The sedimentation rates used in this work were taken directly from the GRILSS dataset, where they were derived primarily from remote sensing

analyses and hydrographic bathymetric surveys. These observations were compiled through an extensive and manually intensive search of diverse and often historical records.

Although expressing sedimentation in areal or mass-normalized units (e.g., mm/year or kg/m²/year) could facilitate inter-site comparison, such normalization would require assuming a constant sediment density and a contributing catchment area that may not represent actual sediment delivery, especially in basins with multiple upstream reservoirs. To maintain consistency with observed data and minimize propagated uncertainty, all rates in this study are reported in volumetric units (MCM/year) as provided in the GRILSS dataset.

For RECLAIM, we considered two complementary aspects of reservoir sedimentation. Capacity Loss Rate (CLR) measures the relative reduction in storage compared to the original built capacity and serves as a qualitative indicator. Sedimentation Rate (SR) quantifies the absolute volume of sediment accumulation, providing a quantitative perspective. The relationship between these variables is shown in Equation 5.1.

$$\text{Capacity Loss Rate} = \frac{\text{Sedimentation Rate}}{\text{Original Built Capacity}} * 100 \quad (5.1)$$

To support qualitative prediction, CLR was further classified into four categories—Low, Medium, High, and Severe—forming the Capacity Loss Type (CLT). The classification ensured sufficient observations in each class while distinguishing reservoirs with higher sedimentation risk. Figure 5.2 presents a boxplot of CLR and the corresponding classes of CLT, Table 5.1 summarizes its four classes, and Table 5.2 lists all potential target variables derived from GRILSS. Since sedimentation rates are time-dependent, GRILSS also provides information on the observation period from which each rate was derived and is therefore included in Table 5.2.

Table 5.1 Different classes of Capacity Loss Type (CLT).

Class Label	Range of CLR (in %/year)	Reservoir Lifespan (in years)	Number of Observations
Low	<0.5	>200	716
Medium	>=0.5 and <1	<=200 and >100	301
High	>=1 and <2.25	<=100 and >44	211
Severe	>=2.25	<=44	140

Table 5.2 Description of sediment data related variables derived from the GRILSS v1.2 dataset (Minocha and Hossain, 2025a).

No.	Name	Abbreviation	Description	Units
T1	Capacity Loss Rate	CLR	Percentage rate of original design capacity lost due to sedimentation during the observed timeframe.	%/year
T2	Capacity Loss Type	CLT	Classification type of CLR as one of the 4 categories (Low, Medium, High and Severe).	-
T3	Sedimentation Rate	SR	Estimated amount of sedimentation rate during the observed timeframe	Million Cubic Meter (MCM)/year
D1	Number of Years	#YR	Number of years in the observed time frame	-
D2	Observation Start Year	OSY	Year of start of observed timeframe	-
D3	Observation End Year	OEY	Year of end of observed timeframe	-

5.4.2. Static Features

Static features represent long-term physical, design, and catchment attributes that remain relatively constant over time. These are described next.

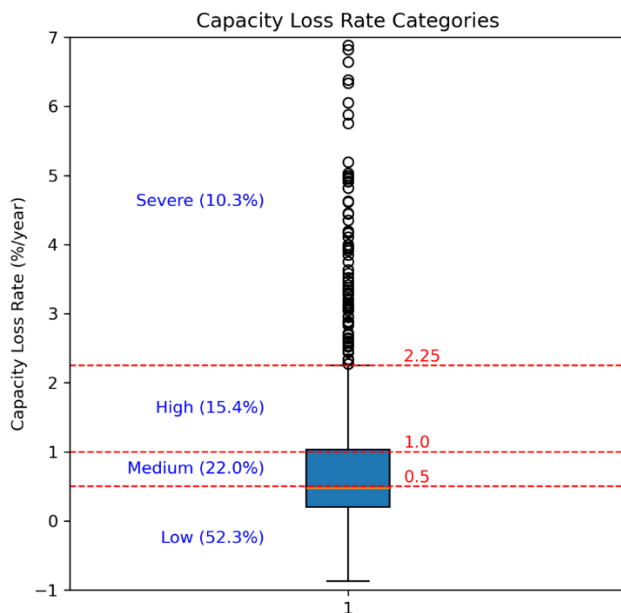


Figure 5.2 Boxplot of reservoir capacity loss rate (CLR), showing the four categories—Low, Medium, High, and Severe—used to define the Capacity Loss Type (CLT) for classification in machine learning models.

5.4.2.1. Reservoir Attributes

In addition to sedimentation rates and their associated observation periods, GRILSS v1.2 (Minocha and Hossain, 2025b) provides several reservoir-specific attributes (mentioned in Table 5.3), including Built Year (BY), Original Built Capacity (OBC), and Impoundment Height (HGT). The dataset also identifies the Major River Basin (MRB) for each reservoir, along with spatial information such as dam point locations, reservoir polygons, and catchment boundaries.

Using these reservoir polygons, additional parameters relevant to sedimentation processes were derived. Specifically, we calculated the reservoir's nominal area (RA) and perimeter (RP), as well as flow length (FL), defined as the shortest hydrological path between the primary reservoir inlet and the dam outlet within the reservoir polygon. While the pre-impoundment river thalweg would ideally represent the natural flow path, such information is generally unavailable at a global scale due to submergence following reservoir creation. Flow length was therefore estimated using

Python-based modules as a consistent and reproducible proxy. Figure 5.3 illustrates examples of flow length estimation for two reservoirs.

The inclusion of this variable is based on the hypothesis that longer flow paths increase the residence time of suspended sediments, allowing greater opportunity for deposition before reaching the dam, whereas shorter paths may correspond to reduced sediment settling.

Area-Elevation curve (AEC) for all reservoirs were also derived using Reservoir Assessment Tool (RAT) (Minocha et al., 2025). It uses digital elevation model called Shuttle Radar Topography Mission (SRTM) hosted in Google Earth Engine (Jarvis et al., 2008). Using the AEC, the mean slope and curvature of AEC were estimated to include features based on the bathymetry of the reservoir which can play a key role in reservoir sedimentation (Table 5.4).

Table 5.3 Description of static reservoir and catchment attributes derived from the GRILSS v1.2 dataset (Minocha and Hossain, 2025a).

No.	Name	Abbreviation	Description	Units
D4	Built Year	BY	Year in which the construction of reservoir finished	-
P1	Original Built Capacity	OBC	Original design capacity of the reservoir	million cubic meter (mcm)
P2	Dam Height	HGT	Height of the impoundment of the reservoir	meter
P3	Major River Basin	MRB	Name of the major river basin in which the reservoir is located.	-
P4	Latitude	LAT	Geographical latitude of the impoundment of the reservoir	degree
P5	Longitude	LON	Geographical longitude of the impoundment of the reservoir	degree
P6	Reservoir Area	RA	Nominal surface area of reservoir estimated using reservoir polygon	sq km
P7	Reservoir Perimeter	RP	Nominal perimeter of the reservoir estimated using reservoir polygon	km
P8	Flow Length	FL	Shortest distance from reservoir inlet to dam outlet within reservoir	km

P9	Catchment Area	CA	Catchment area of the reservoir	km ²
P10	Differential Catchment area	DCA	Incremental catchment area of the reservoir that does not account for catchment area of upstream reservoirs.	sq km

Table 5.4 Description of static reservoir attributes related to its Area-Elevation curve (AEC) derived from Reservoir Assessment Tool (Minocha et al., 2025). “DL” stands for dimensionless units.

No.	Name	Abbreviation	Description	Units
P11	AEC Slope	AECS	Mean slope of the AEC, representing the average rate of change in reservoir surface area with elevation.	km ² /m
P12	AEC Curvature	AECC	Mean curvature of the AEC, describing whether the relationship between surface area and elevation is predominantly convex or concave.	km ² /m ²
P13	AEC Concavity Index	AECI	Ratio of the area under the straight line connecting minimum and maximum elevations to the area under the actual AEC curve.	DL

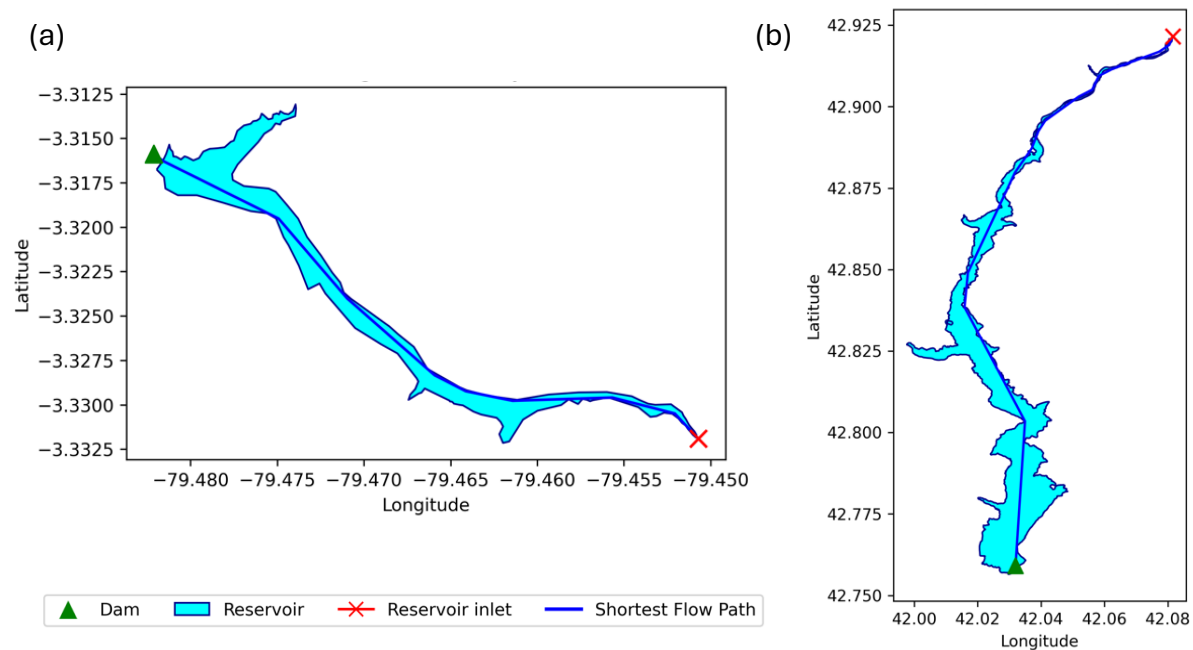


Figure 5.3 Examples of the shortest flow path estimated for two reservoirs, where the path length is defined as flow length (FL). **(a)** Minas–San Francisco Reservoir, Ecuador. **(b)** Jvari Reservoir, Georgia . The locations of both reservoirs are shown in Figure 5.1.

5.4.2.2. Catchment Attributes

Catchment characteristics are a key determinant of sediment delivery into reservoirs. GRILSS v1.2 provides the total catchment area (CA) for each reservoir (Table 5.3). To extend this information, we derived the differential catchment area (DCA) by combining GRILSS with the high-resolution (15 arc second) HydroSHEDS flow direction dataset (Lehner et al., 2008) and the ResORR (Reservoir Operations driven River Regulation) network algorithm (Das et al., 2024; Minocha et al., 2024). This procedure identified immediate upstream dams and subtracted their drainage areas from that of the focal reservoir. The resulting DCA approximates the effective sediment-contributing area, recognizing that upstream dams may retain part of the sediment load. Since accounting for every upstream dam globally is not feasible, only dams included in GRILSS were considered to test whether DCA substantially influences sedimentation rates. Beyond CA and DCA (Table 5.3), additional attributes were derived from global datasets and catchment polygons, including land cover, land use, soil type, and terrain characteristics.

For land-cover–based attributes, we used the *Global Land Cover-SHARE (GLC-SHARE)* database developed by the Food and Agriculture Organization (FAO) of the United Nations, which provides global land cover data at 30 arc-second (~1 km²) resolution (FAO, 2014). GLC-SHARE defines 11 land cover categories: (1) artificial surfaces, (2) cropland, (3) grassland, (4) tree-covered areas, (5) shrub-covered areas, (6) herbaceous vegetation (aquatic or regularly flooded), (7) mangroves, (8) sparse vegetation, (9) bare soil, (10) snow and glaciers, and (11) water bodies. The features derived from this dataset are listed in Table 11.1 (Appendix) and mainly include the percentage of catchment for each land cover type and the dominant land cover in the catchment. While land cover is not strictly static, relative proportions within a catchment generally remain stable over time. The dynamic component of land use and land cover change is addressed in Section 5.4.3.2.

In addition to land cover, we also considered soil and terrain characteristics as static catchment attributes. Soil-related features were derived from the *Harmonized World Soil Database (HWSD v2.0)* developed by FAO, which provides information on soil properties at 1 km resolution (FAO, 2023). From this dataset, attributes related to bulk soil density and soil composition were extracted (Table 11.5 in Appendix). Terrain attributes were obtained from the global topography grid *SRTM30_Plus* at 30 arc-second (~1 km) resolution (Becker et al., 2009). For each catchment, the mean elevation, slope, aspect, curvature, and hillshade were computed and are summarized in Table 11.2 (in Appendix).

Table 5.5 Description of catchment attributes derived from the *Harmonized World Soil Database (HWSD v2.0)* dataset (FAO, 2023).

No.	Name	Abbreviation	Description	Units
P26	Coarse composition	COAR	Mean percentage of coarse particles in the soil aggregated over the catchment.	%
P27	Sand composition	SAND	Mean percentage of sand in the soil aggregated over the catchment.	%
P28	Silt composition	SILT	Mean percentage of silt in the soil aggregated over the catchment.	%
P29	Clay composition	CLAY	Mean percentage of clay in the soil aggregated over the catchment.	%
P30	Bulk soil density	BULK	Mean bulk density of the soil aggregated over the catchment.	g/cm ³

5.4.3. Dynamic Features

Dynamic features capture the temporal variability in hydrological, climatic and catchment conditions that influence sedimentation processes over time. To ensure temporal consistency between predictor variables and sedimentation observations, all dynamic features derived from satellite data were restricted to the period of available Earth observations (1984–2023). For reservoirs where sedimentation rates were reported over longer historical periods, including years prior to 1984, the effective observation window was limited to the overlapping period with satellite data. All dynamic predictors were then summarized using statistical metrics (e.g., mean, standard deviation) over this period.

This approach ensures that the model learns relationships based solely on satellite-observable conditions, enabling consistency and scalability across global datasets. While this may introduce some underestimation in cases where earlier periods experienced higher sedimentation rates, it avoids incorporating biases from non-satellite or inconsistently available historical data sources.

5.4.3.1. Reservoir Dynamics

Sediment transport within reservoirs is closely linked to the dynamics of stored water. The rate at which water enters, leaves, and is retained in a reservoir directly affects how much suspended sediment settles on the reservoir bed. Longer residence times generally increase the likelihood of sediment deposition. To capture these dynamics, time series of key hydrological variables—including inflow, outflow, surface area, and evaporation—were generated for each reservoir using the Reservoir Assessment Tool (RAT) 3.0 (Minocha et al., 2024).

Several prior studies have demonstrated satellite-based estimation of reservoir surface area and storage dynamics at regional scales (e.g., Vu et al., 2022). RAT is, to the best of our knowledge, the only globally scalable and distributed Python package that enables easy and computationally efficient tracking of reservoir water surface area and water level changes worldwide (Minocha et al., 2025).

In addition to hydrological fluxes, we also sought to represent the dynamics of suspended sediments in reservoirs. Direct estimation of suspended sediment concentration (SSC) from remote sensing has been studied extensively and typically requires calibration with in-situ data for each region (Adjovu et al., 2023; Adamo et al., 2021; Beveridge et al., 2020a, 2020b). For a global-scale application, however, such calibration is not feasible. Instead, our approach was to derive a normalized metric—Normalized Suspended Sediment Concentration (NSSC)—from satellite data. NSSC (described next) does not provide absolute concentrations but serves as a qualitative indicator of relative sediment levels suitable for machine learning applications.

For this study, NSSC was derived using remotely sensed surface reflectance data. Two indices were calculated: (i) the mean ratio of red to green bands (NSSC1) and (ii) the mean ratio of near infrared to red bands (NSSC2) (Wackerman et al., 2017; Pereira et al., 2019; Beveridge et al., 2020a). For each reservoir, the corresponding shapefile polygon defined the region of interest, within which time series of these ratios were extracted and subsequently normalized using minimum and maximum estimated values.

NSSC1 and NSSC2 are now implemented in the current RAT package (version 3.0.18), enabling users to generate these indicators alongside standard reservoir dynamics outputs. Incidentally, this represents the first global-scale integration of remotely sensed SSC into a reservoir monitoring framework, to the best of our knowledge. It also extends RAT’s functionality beyond water balance dynamics to include sediment dynamics. Table 5.6 lists all the reservoir specific time-series data derived using RAT.

Table 5.6 Description of the time-series associated with reservoir dynamics derived using Reservoir Assessment Tool (RAT) (Minocha et al., 2025). “DL” stands for dimensionless units.

Time-Series	Data Products used by RAT	Frequency	Duration	Units
Inflow	ERA-5 (Hersbach et al., 2020); NCEP/NCAR (Kalnay et al., 1996)	daily	1984-2023	m ³ /day
Outflow	-	4-16 days	1984-2023	m ³ /day
Surface Area	Landsat 5,7,8,9 + Sentinel 2 + Sentinel 1	4-16 days	1984-2023	km ²
Evaporation	NCEP/NCAR (Kalnay et al., 1996)	daily	1984-2023	mm
NSSC1 (near-infrared/red band)	Landsat 5,7,8,9 + Sentinel 2 + Sentinel 1	8-16 days	1984-2023	DL

NSSC2 (red/green band)	Landsat 5,7,8,9 + Sentinel 2 + Sentinel 1	8-16 days	1984-2023	DL
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Since the target variable of the machine learning model is reservoir sedimentation rate or capacity loss rate, the raw time series in Table 5.6 could not be used directly. Instead, key statistical metrics were derived for each reservoir from the different time series, including mean, standard deviation, coefficient of variation, skewness, and kurtosis, calculated annually and then averaged over a certain period. Complete list of these attributes with their description is mentioned in Table 11.3 (Appendix). Some metrics were computed over the full period of record (1984–2023), while others were restricted to the specific observation window of sedimentation, defined by observation start (OSY) and end (OEY) year in Table 5.2. For instance, long-term surface area trends can serve as a proxy for reservoir operation practices—hydropower reservoirs, for example, are typically maintained near full supply levels—making them suitable for estimation over multiple decades. In contrast, flux-related metrics were derived only over the sedimentation observation window to ensure compatibility with the target variable.

5.4.3.2. Catchment Dynamics

To capture the dynamic aspects of catchment conditions, we considered both land use change and meteorological variability.

For land use, we used the HILDA+ (Historic Land Dynamics Assessment+) dataset, which provides annual global land use/cover data from 1960 to 2019 at 1 km spatial resolution (Winkler et al., 2021). HILDA+ classifies land into six categories: (1) urban areas, (2) cropland, (3) pasture/rangeland, (4) forest, (5) unmanaged grass/shrubland, and (6) sparse/no vegetation. From this dataset, we quantified long-term vegetation gain and vegetation loss frequency over the past 60 years. For example, a transition from cropland to urban areas was treated as vegetation loss, while a transition from cropland to forest was considered vegetation gain. Table 11.4 (Appendix) lists these land cover–based attributes derived from HILDA+.

In addition, we incorporated meteorological drivers that influence catchment erosion and, in turn, reservoir sedimentation. For each catchment, four decades (1984–2023) of precipitation, temperature, and wind time series were derived using the Reservoir Assessment Tool (RAT) (Minocha et al., 2024) and are summarized in Table 5.7. From these time series, we extracted key statistical measures—including mean, standard deviation, skewness, kurtosis, and coefficient of variation—as predictor variables. For precipitation, additional indicators were developed, such as the number of days exceeding 10 mm and 50 mm thresholds. The complete set of meteorology-based attributes is provided in Table 11.5 (Appendix).

Table 5.7 Description of the time-series associated with catchment dynamics derived using Reservoir Assessment Tool (RAT) (Minocha et al., 2025).

Time-Series	Data Products used by RAT	Frequency	Duration	Units
Precipitation	ERA-5 (Hersbach et al., 2020)	daily	1984-2023	mm
Minimum Temperature	NCEP/NCAR (Kalnay et al., 1996)	daily	1984-2023	°C
Maximum Temperature	NCEP/NCAR (Kalnay et al., 1996)	daily	1984-2023	°C
Wind Speed	NCEP/NCAR (Kalnay et al., 1996)	daily	1984-2023	m/s

5.5. Data Processing

After compiling all variables, the dataset was processed to address missing values, perform feature transformations, and generate additional features through feature engineering. In particular, some reservoirs—mainly dry dams—did not have reservoir polygons in the GRILSS dataset (Minocha and Hossain, 2025a). This absence led to missing values for variables that relied on polygon-based information. Missing data were handled systematically, with special treatment for key variables such as dam height (details provided in Appendix Section 11.1). In addition, certain variables were

transformed to reduce skewness and improve their suitability for machine learning. The following subsections describe the procedures for feature engineering, and feature transformation.

5.5.1. Feature Engineering

The performance of data-driven models such as machine learning depends strongly on the quality and relevance of the features used for training. To enhance the predictive capability of RECLAIM, we derived new features from the raw variables described in Section 5.4, a process commonly referred to as feature engineering. These derived features were designed to capture underlying processes relevant to reservoir sedimentation that are not directly represented in the raw variables. A summary of all derived features is provided in Table 11.6 (Appendix).

5.5.1.1. Reservoir Characteristics

Reservoir age can influence sedimentation, as older reservoirs often experience lower capacity loss rates. This is primarily because sediment has already accumulated over time, reducing the effective storage capacity available for additional deposition. Reservoir age at the time of observation was calculated as the difference between the observation end year (OEY, Table 5.2) and the built year (BY, Table 5.3).

To capture size-normalized storage, relative capacity was computed as the ratio of original built capacity to catchment area. Additionally, reservoir geometry can influence sediment deposition, with more complex shapes generally promoting higher sediment deposition (Kantoush, 2008; Mohammadzadeh-Habili, 2021). Reservoir geometry complexity was estimated as the ratio of reservoir area (RA) to the square of reservoir perimeter (RP^2).

5.5.1.2. Vegetation and Land cover

For each reservoir, the absolute catchment area of different land cover types (Table 11.1, Appendix) was computed by multiplying the percentage of land cover with the total catchment area. Using dynamic land-use and land-cover features (Table 11.4, Appendix), we further

derived net vegetation gain frequency during 1960-2019 to capture temporal changes in catchment vegetation.

5.5.2. Feature Ratios

Ratios between features often provide more insight than absolute values. The following ratios were computed for RECLAIM:

- The ratio of tree-covered area to bare soil, and shrubs to bare soil, may better reflect soil erosion potential than the individual areas.
- The ratio of coarse particles to sand in the catchment indicates textural composition influencing sediment delivery.
- The ratio of annual mean surface area of reservoir observed from satellites (SA_mean_clip, Table 11.3 in Appendix) to the nominal reservoir area (RA, Table 5.3) reflects reservoir filling relative to full capacity. A similar proxy can be obtained by taking ratio of annual mean surface area to original built capacity.
- The ratio of mean annual rainfall to catchment area was computed to estimated rainfall per unit area.

5.5.3. Hydrological Variables

Hydrological metrics were derived to capture processes directly linked to sediment transport and deposition. Residence time, representing the average duration a water parcel remains in a reservoir, was estimated as the ratio of original built capacity to mean annual inflow. Trapping efficiency was calculated using an approximation of the median Brune curve, as given by Siyam (Equation 5.2), where TE represents trapping efficiency, capacity is the original built capacity (MCM), and inflow is the mean annual inflow (MCM) (Brune, 1953; Siyam, 2000; Revel et al., 2015).

$$TE = 100 * e^{-0.0079 \left(\frac{\text{inflow}}{\text{capacity}} \right)} \quad 5.2$$

Using this trapping efficiency, estimated capacity loss rate (ECLR, Table 11.6 in Appendix) and estimated sedimentation rate (ESR, Table 11.6 in Appendix) due to suspended sediments was computed using Equation 5.3 and 5.1, respectively, where NSSC is the mean annual NSSC, and the other variables are same as Equation 5.2. Additionally, sediment influx and outflux were computed as the product of mean annual NSSC with mean annual inflow and outflow, respectively. It should be noted that, unlike SSC, NSSC is dimensionless and is used here as a relative quantity rather than an absolute measure.

$$ECLR = TE * \frac{NSSC * inflow}{capacity} \quad 5.3$$

NSSC_2, based on the red-to-green band ratio, was selected for Equation 5.3 due to its demonstrated robustness in estimating suspended sediment concentrations in inland waters, particularly under low to moderate turbidity conditions that are typical of most reservoir systems. This spectral relationship has been widely adopted due to its sensitivity to variations in sediment concentration while maintaining stability across diverse optical environments (e.g., Nechad et al., 2010; Li et al., 2019). In contrast, band combinations involving near-infrared (NIR) and red wavelengths, such as those used in NSSC_1, tend to perform better under highly turbid conditions and are more suitable for extreme sediment concentrations.

5.5.4. Feature Transformation

Feature transformation was carried out to ensure that variables were more informative and suitable for model training. Categorical variables such as major river basin (MRB, Table 5.3), dominant land cover (DLC, Table 11.1), and capacity loss type (CLT, Table 5.1) were encoded with unique integer values to represent each class. For MRB, the HydroSHEDS provided HYBASID was used as the unique identifier (Lehner et al., 2008).

Several continuous variables exhibited high skewness, particularly those related to spatial dimensions (e.g., capacity, area, and length). To address this, a natural log transformation was applied. The effect of this transformation is illustrated in Figure 5.4, where skewness reduction is

shown for original built capacity (OBC, Table 5.3) and catchment area (CA, Table 5.3). A complete list of log-transformed variables is provided in Table 11.7 (Appendix). The original variable names were retained following transformation to ensure consistency across tables and figures.

Negative values of capacity loss rate (CLR) and sedimentation rate (SR), which can arise from sediment management interventions or short observation periods (Minocha and Hossain, 2025a), were replaced with small nonzero values (0.01 %/year for CLR and 0 MCM/year for SR). This adjustment ensures that the models do not attempt to learn physically implausible negative values, while still preserving the integrity of the dataset.

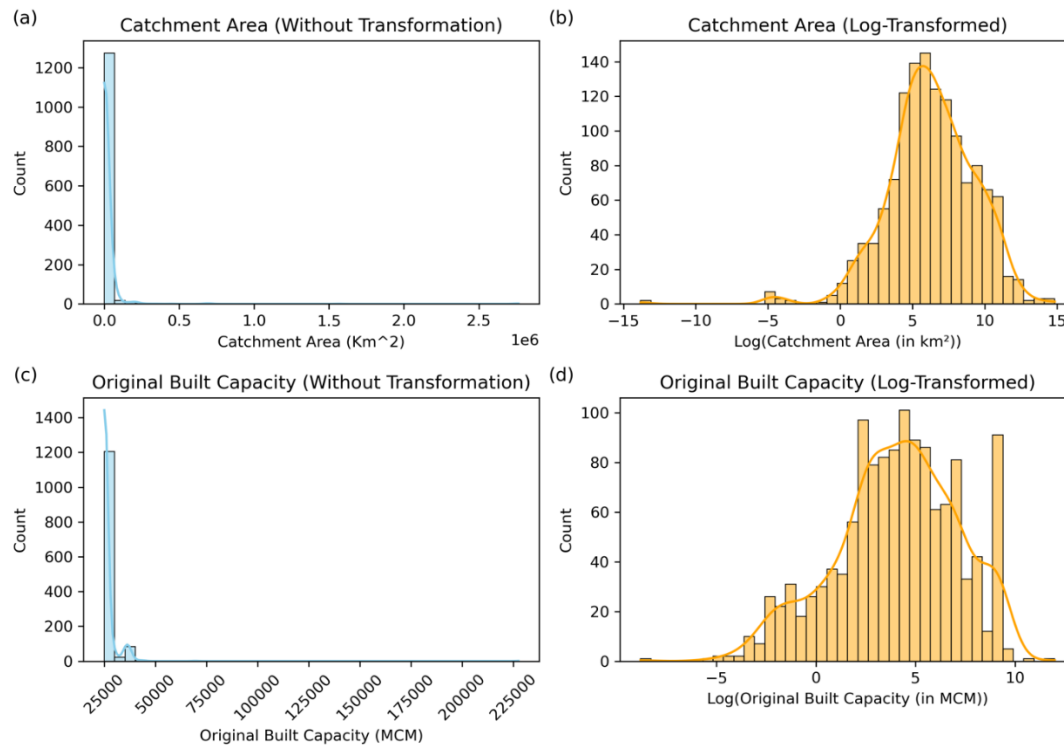


Figure 5.4 **(a) and (c)** Frequency distributions of reservoir catchment area and original built capacity (untransformed). **(b) and (d)** Frequency distributions of the same variables after log transformation, which reduces skewness and normalizes the distributions.

5.6. Model Training and Development

Traditional approaches for estimating reservoir sedimentation, including empirical relationships (e.g., trap efficiency curves) and site-specific statistical regressions, are often limited by simplified assumptions, reliance on localized calibration, and the need for field-based measurements that are not consistently available at large scales (Brune, 1953; Morris and Fan, 1998). As a result, their applicability for global or cross-regional assessments remains constrained.

To address these limitations, RECLAIM leverages globally available satellite-derived features together with curated in-situ observations, enabling predictions without site-specific calibration. Its machine learning framework is designed to capture nonlinear interactions among hydrological, climatic, and geomorphological drivers, while remaining computationally efficient once trained. This makes RECLAIM particularly suited as a scalable, screening-level tool for prioritizing reservoirs for detailed surveys and management interventions.

Following this design, the model was trained and evaluated using the compiled dataset described in Section 5.4. The final dataset comprised 88 predictor features, three target variables, and 1,315 reservoir-level observations for 984 distinct reservoirs. For data-driven models such as RECLAIM, rigorous evaluation requires testing on data not seen during training. To ensure this, the dataset was partitioned into three subsets: training (80%), validation (10%), and test (10%). Care was taken to prevent the same reservoir from appearing across multiple subsets, thereby avoiding data leakage and artificially inflated performance.

The training dataset was used to fit machine learning models, with the validation set employed for hyperparameter tuning and the test set reserved for final evaluation. In this study, we applied three widely used and powerful gradient boosting algorithms: XGBoost, LightGBM, and CatBoost (Chen and Guestrin, 2016; Ke et al., 2017 and Prokhorenkova et al., 2018). These methods are particularly advantageous for tabular datasets because they capture complex nonlinear relationships, handle missing values effectively, and are relatively robust to feature scaling. They also tend to outperform deep learning approaches on relatively small datasets such as ours (~1,300 observations), which typically require larger training samples to generalize effectively (Huber et al., 2022).

In preliminary analysis, we also evaluated Random Forest and neural network-based models, but both showed lower predictive performance. This is likely due to the limited sample size and heterogeneous feature space. Consistent with prior studies on tabular data (Shwartz-Ziv and Armon, 2022), gradient boosting methods performed best and are therefore adopted in this study.

We chose to evaluate all three algorithms because, while they share a common gradient boosting framework, each has unique strengths: XGBoost is well-established and known for its flexibility and regularization options; LightGBM is optimized for efficiency and scalability, particularly with large feature spaces; and CatBoost is designed to handle categorical variables effectively and reduce overfitting through ordered boosting. By comparing their performance, we ensured that RECLAIM was built on the most suitable algorithm for predicting reservoir sedimentation.

The sensitivity of RECLAIM model performance to data partitioning was also evaluated by conducting a 10-fold cross-validation analysis on the combined train and validation set (90% of total dataset), ensuring that individual reservoirs were not shared between training and validation sets within any fold. This approach preserves independence across reservoirs while enabling assessment of model stability across multiple data splits. We next describe the prediction of Capacity Loss Rate (CLR) and Sedimentation Rate (SR) in Sections 5.6.1 and 5.6.2.

5.6.1. Capacity Loss Rate

As capacity loss rate (CLR) is a relative measure, it can serve both as a continuous regression target and as a categorical classification target as described in Section 5.4.1.

5.6.1.1. Classification

As described in Section 5.4.1, CLR was categorized into four classes—Low, Medium, High, and Severe—collectively referred to as Capacity Loss Type (CLT). Figure 5.5 summarizes the classification performance of the three models, both overall and by class. The models demonstrated

broadly similar performance, with CatBoost performing slightly better than the others. Classification accuracy, however, varied substantially across classes: the Medium and High categories were the most difficult to predict, while the Severe class was consistently identified with the highest accuracy. Overall accuracy ranged from 55%–57% on the test set and approximately 61% on the validation set, with CatBoost reaching 75% (test) and 80% (validation) for the Severe class. Although the overall performance remains modest, the models' ability to reliably flag reservoirs with extremely high capacity loss (Severe class) is encouraging, as these cases represent the greatest management priority.

5.6.1.2. Regression

We also attempted to predict exact capacity loss rate (CLR) values using the three gradient boosting regressors. Figure 5.6 compares observed and predicted CLR for validation and test datasets. Across all models, performance is broadly similar, with XGBoost and CatBoost showing slightly lower prediction errors than LightGBM. On the test set, mean absolute errors (MAE) are consistently around 0.82–0.87% per year, which is relatively small when compared to the standard deviation of the observed target (~3.5% per year). This indicates that, in absolute terms, the models are producing reasonably accurate predictions.

However, the coefficient of determination (R^2) remains modest, nearly 0.27 on the test set. This is primarily a consequence of the very high variance of CLR in the dataset (variance = 12.32). In such cases, even a model that meaningfully reduces prediction error may not achieve high R^2 , since much of the observed variability is dominated by a few extreme outliers. Thus, while the models reduce average error, they capture only a limited share of the total variability.

It is also important to note that the CLR distribution is heavily skewed: as already shown in Figure 5.2, about 76% of reservoirs have CLR below 1% per year, and nearly 90% below 2% per year. The high variance therefore arises from a small number of reservoirs with unusually high loss rates. In this context, even though the regression models achieve sub-1% errors on average, this performance offers limited added value compared to simply predicting the global mean (~1% per

year). For RECLAIM, the ability to distinguish cases of unusually high sedimentation is far more valuable than minimizing average error, which explains why CLR may not be the most informative target metric for predictive modeling.

Alternative loss functions designed for skewed distributions, including Tweedie and Huber losses (So and Valdez, 2024; Huber, 1992), were also evaluated but did not improve CLR model performance (Table 11.8 in Appendix). This further indicates that the relatively low predictive skill of CLR is not primarily driven by loss function choice, but reflects its inherent limitations as a predictand.

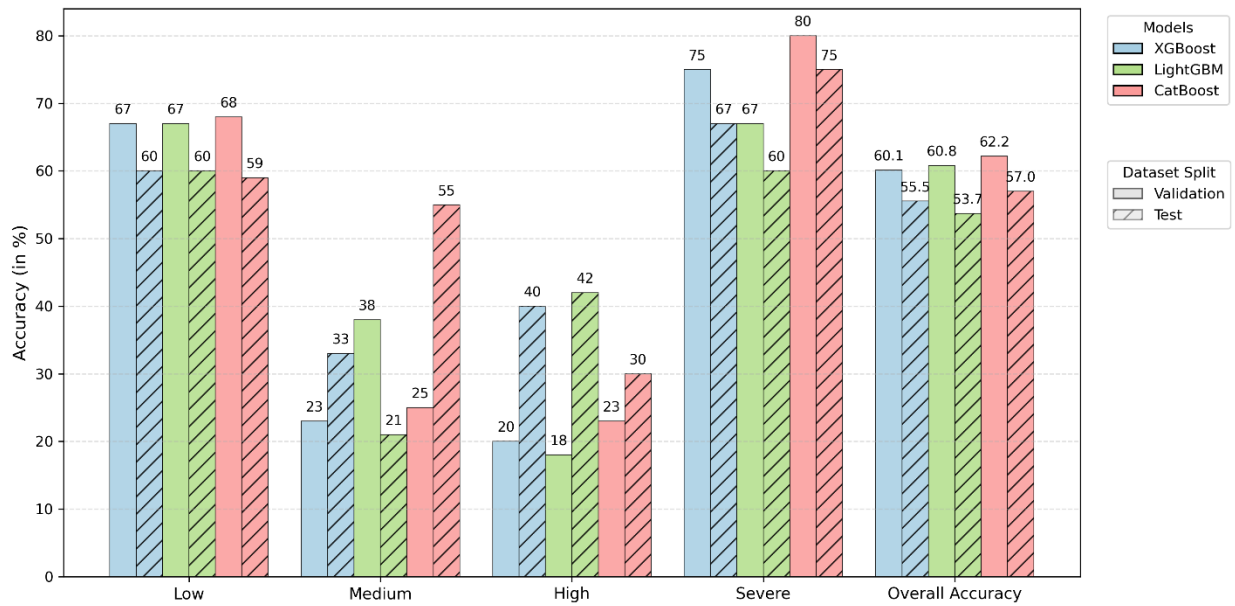


Figure 5.5 Classification performance of the four capacity loss type (CLT) classes across validation and test sets for three gradient boosting models.

5.6.2. Sedimentation Rate

Sedimentation rate (SR), expressed as an absolute quantity in million cubic meters per year (MCM/year), cannot be treated as a classification target and was therefore modeled exclusively as a regression problem using the three gradient boosting algorithms. As shown in Figure 5.7, SR exhibits a highly skewed distribution, with most reservoirs experiencing low sedimentation rates

and only a few with extremely high values. Standard regression loss functions (such as mean squared error) struggled to learn from this distribution, so specialized approaches were adopted.

For XGBoost and LightGBM, we employed the Tweedie loss function (So and Valdez, 2024; Manna et al., 2025), which is particularly suited for data that combine many small values with occasional very large ones—common in rainfall, insurance claims, or in our case, reservoir sedimentation. Tweedie loss function essentially balances between modeling continuous values and rare extreme events. For CatBoost, we used the Huber loss function (Huber, 1992), which behaves like mean squared error for most values but switches to mean absolute error for large deviations, thereby reducing the influence of outliers while still capturing the overall pattern.

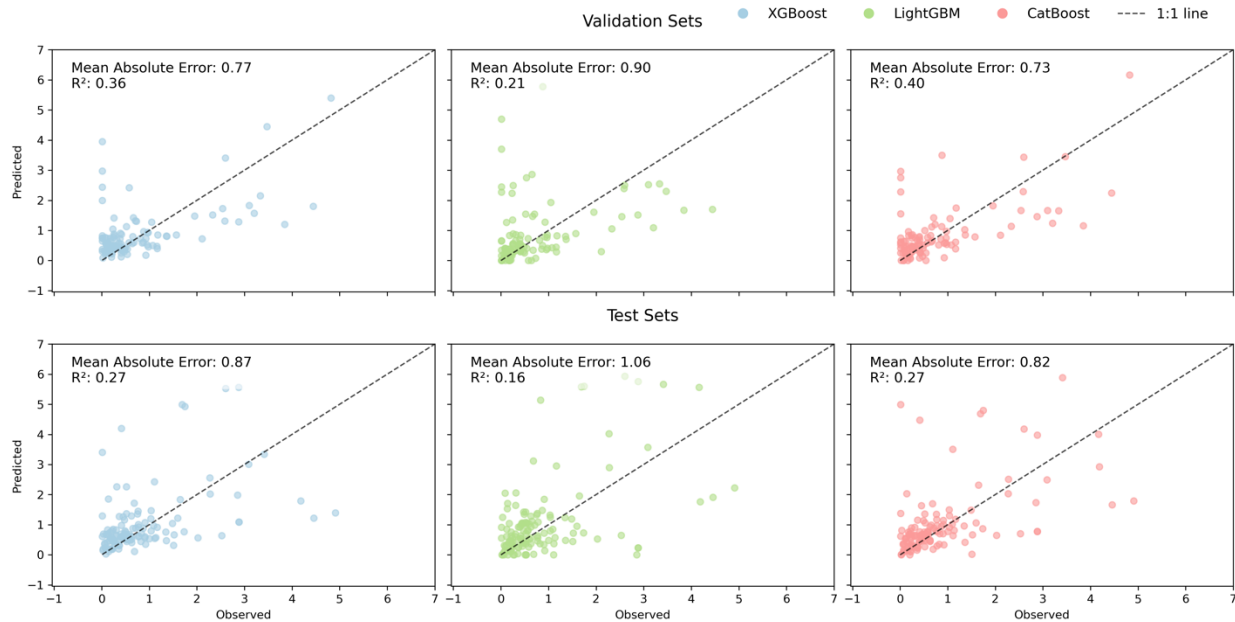


Figure 5.6 Regression performance for capacity loss rate (CLR) as the target across validation and test sets for three gradient boosting models. Mean absolute error (MAE) in % per year and coefficient of determination (R^2) are reported for each case.

Figure 5.8 presents the predictive performance of the three models on validation and test sets. Compared to CLR regression or classification, SR predictions were substantially more accurate. CatBoost achieved the best results on the test set, with a mean absolute error (MAE) of 1.66

MCM/year and an R^2 of 0.86. XGBoost and LightGBM performed similarly, with MAE values around 1.89 MCM/year and R^2 values near 0.82. These error levels are small relative to the mean SR (4.79 MCM/year) and its high standard deviation (14.5 MCM/year), indicating that the models captured both central tendencies and much of the variability in sedimentation rates. Importantly, the ML models were also able to predict reservoirs with very high SR values, demonstrating robustness across the distribution.

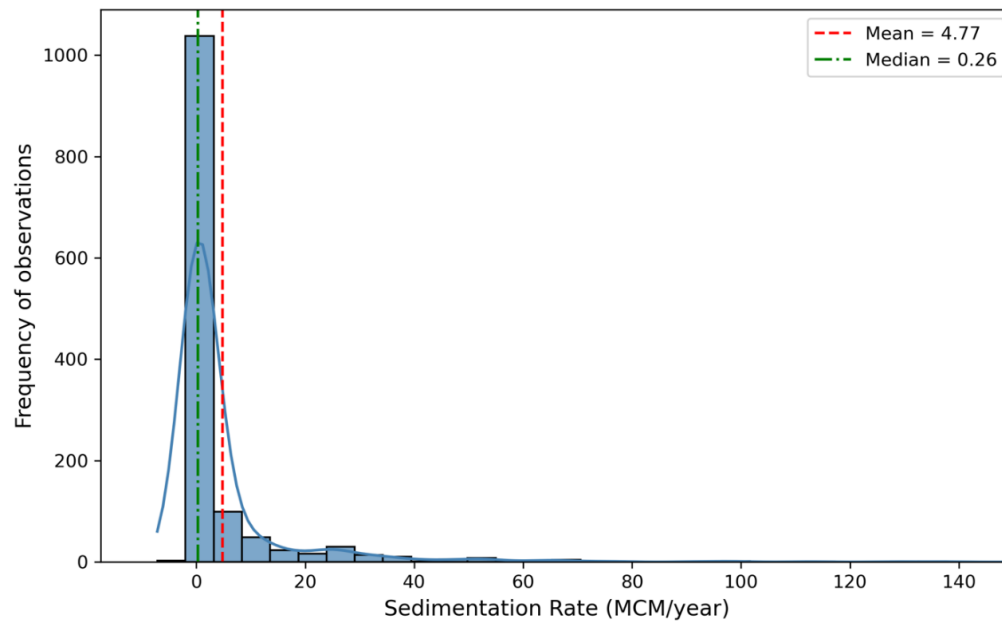


Figure 5.7 Frequency distribution of reservoir sedimentation rates, showing a high number of values near zero, characteristic of a Tweedie distribution. The blue curve represents the kernel density estimate, with mean and median values indicated.

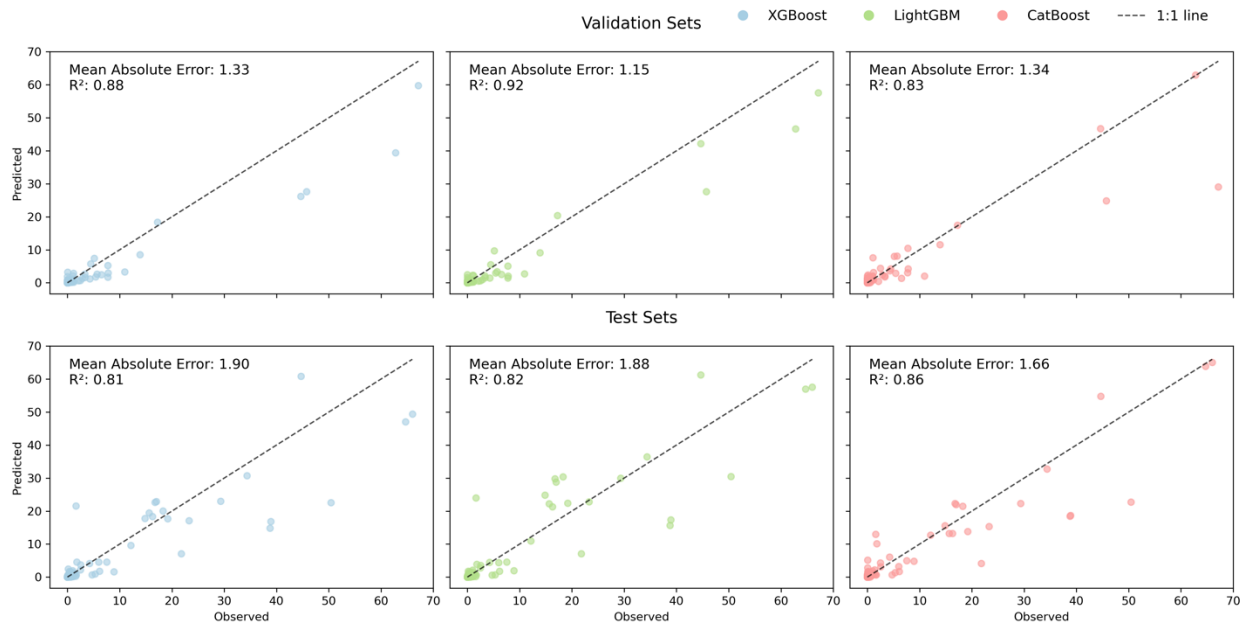


Figure 5.8 Regression performance for sedimentation rate (SR) as the target across validation and test sets for three gradient boosting models. Mean absolute error (MAE) in MCM/year and coefficient of determination (R^2) are reported for each case.

5.6.3. RECLAIM as an Ensemble of SR-predicting Models

Given the stark differences in predictive skill between capacity loss rate (CLR) and sedimentation rate (SR), only the SR regression models were ultimately integrated into the ensemble framework for RECLAIM. This design choice not only enhanced predictive performance but also broadened the utility of RECLAIM by providing quantitative estimates of capacity loss in physical units (MCM per year), rather than limiting predictions to qualitative categories.

To further improve accuracy and robustness, we developed RECLAIM as a weighted ensemble of the three gradient boosting models. Figure 5.9(a) illustrates the residual patterns across validation data: all three models perform comparably for SR values below ~15 MCM/year, with CatBoost consistently showing marginally superior accuracy. For SR values above 15 MCM/year, however, XGBoost exhibits larger residual errors, while CatBoost and LightGBM emerge as the more reliable predictors.

RECLAIM capitalizes on these complementary strengths by assigning dynamic weights to each model rather than relying on a fixed average. CatBoost serves as the reference model, and its prediction is compared against a user-specified SR threshold (default is 15 MCM/year) to determine the dynamic weights as follows:

- **From zero to threshold:** CatBoost's weight increases gradually from 30% to 55%, XGBoost's weight decreases from 45% to 25%, and LightGBM's weight increases slightly from 25% to 30%.
- **Above the threshold:** CatBoost's weight is fixed at 60%, XGBoost's weight decreases smoothly from 15% to 5%, and LightGBM's weight increases from 25% to 35%. Beyond a saturation point, the weights stabilize and remain constant.

Weights are adjusted using sigmoid scaling functions, ensuring smooth transitions across SR ranges rather than abrupt changes. This dynamic scheme allows RECLAIM to emphasize the most reliable model in each regime while still retaining contributions from all three algorithms. While users may alternatively select single-model predictions or a simple mean ensemble, the dynamic weighting consistently provided the most balanced performance across the full SR spectrum. Figure 5.9(b) compares RECLAIM predictions with observed SR for the training, validation, and test sets, while Table 5.8 reports the error metrics—RMSE, MAE, and R^2 . RECLAIM performs slightly better than CatBoost—the strongest individual model—while also integrating information from all three algorithms, thereby offering a more robust and generalizable solution.

The higher RMSE relative to MAE reflects the influence of a small number of reservoirs with very high sedimentation rates. As shown in Figure 5.7, the SR distribution is highly skewed, with most values concentrated at the lower end and only a few extreme cases. In such settings, even moderate prediction errors for high-SR reservoirs can disproportionately increase RMSE while having a smaller effect on MAE. This pattern is also evident across data partitions (Figure 11.2 in Appendix), indicating that RMSE is primarily sensitive to these sparse extreme observations rather

than systematic model bias. While these cases remain challenging to predict due to their limited representation in the dataset, the model captures the overall magnitude and variability of sedimentation effectively across the majority of reservoirs. Sections 5.6.4 and 5.6.5 next examine RECLAIM's generalizability across data partitions and geographic regions in more detail.

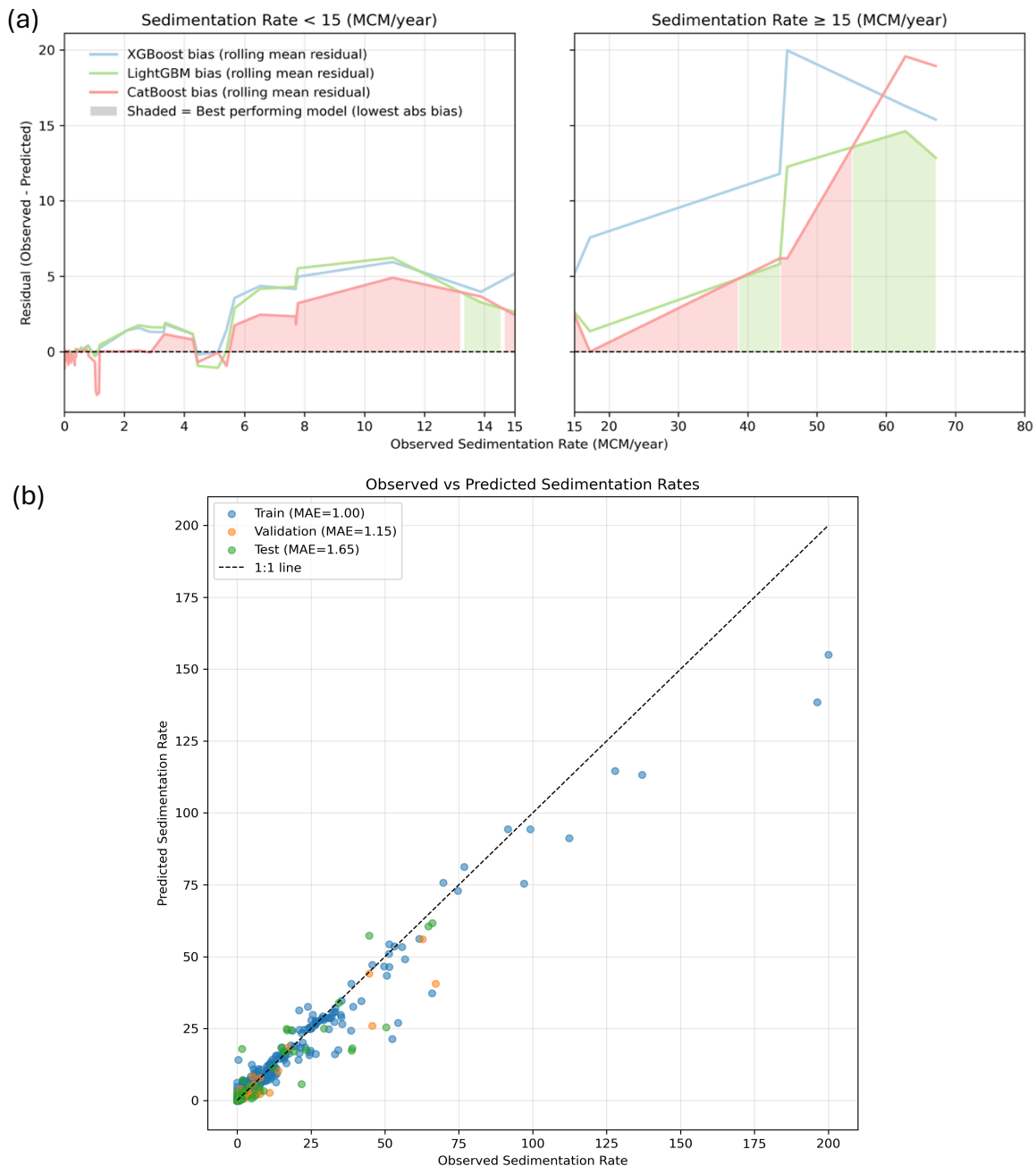


Figure 5.9 (a) Rolling mean of residuals (observed minus predicted) for three gradient boosting models across sedimentation rates. Shaded colors indicate the model with the lowest

absolute residual or bias within each sedimentation range. **(b)** Predictive performance of RECLAIM—an ensemble of XGBoost, CatBoost, and LightGBM—on training, validation, and test sets.

5.6.4. Cross-Validation Generalizability

To assess generalization across different data partitions, a 10-fold group-based cross-validation was conducted for the ensembled RECLAIM model on the combined train and validation set (90% of the dataset), ensuring reservoir independence across folds (full methodology and results provided in Appendix Section 11.2). The cross-validation yielded $RMSE = 7.62 \pm 4.86$ MCM/year and $MAE = 3.13 \pm 1.66$ MCM/year. These values are larger than the fixed test-set metrics ($RMSE = 4.44$, $MAE = 1.65$, $R^2 = 0.86$) primarily because folds containing high-SR reservoirs in the validation set (e.g., Split 1 and Split 3) drive disproportionately large errors, whereas folds with fewer extreme values (e.g., Split 6 and Split 9) perform considerably better (Figure 11.2 in Appendix). This variability reflects the skewed, heavy-tailed distribution of SR rather than sensitivity to a particular data split.

The higher RMSE relative to MAE across all partitions is similarly attributable to the disproportionate influence of a small number of extreme sedimentation events: even moderate prediction errors on these rare high-SR reservoirs inflate RMSE substantially while having a smaller effect on MAE. The cross-validation performance therefore represents the more operationally relevant estimate of generalization for end users deploying RECLAIM on unseen reservoirs, while the fixed test-set results reflect the internal development benchmark used during model selection and tuning.

5.6.5. Spatial Generalizability

To characterize the spatial distribution of prediction errors and address regional reliability, Figure 5.10 maps basin-scale MAE and reservoir-level absolute prediction error globally, with reservoir symbols scaled by storage capacity. It is important to note that these errors are in-sample training errors: the spatial analysis uses the final RECLAIM model trained on 100% of the dataset, so regional patterns reflect the model's fit to all available training data rather than out-of-sample generalization. This approach avoids introducing regional training-data bias into the spatial

interpretation — a distinction that should be borne in mind when comparing these figures to the cross-validation metrics reported in Section 5.6.4.

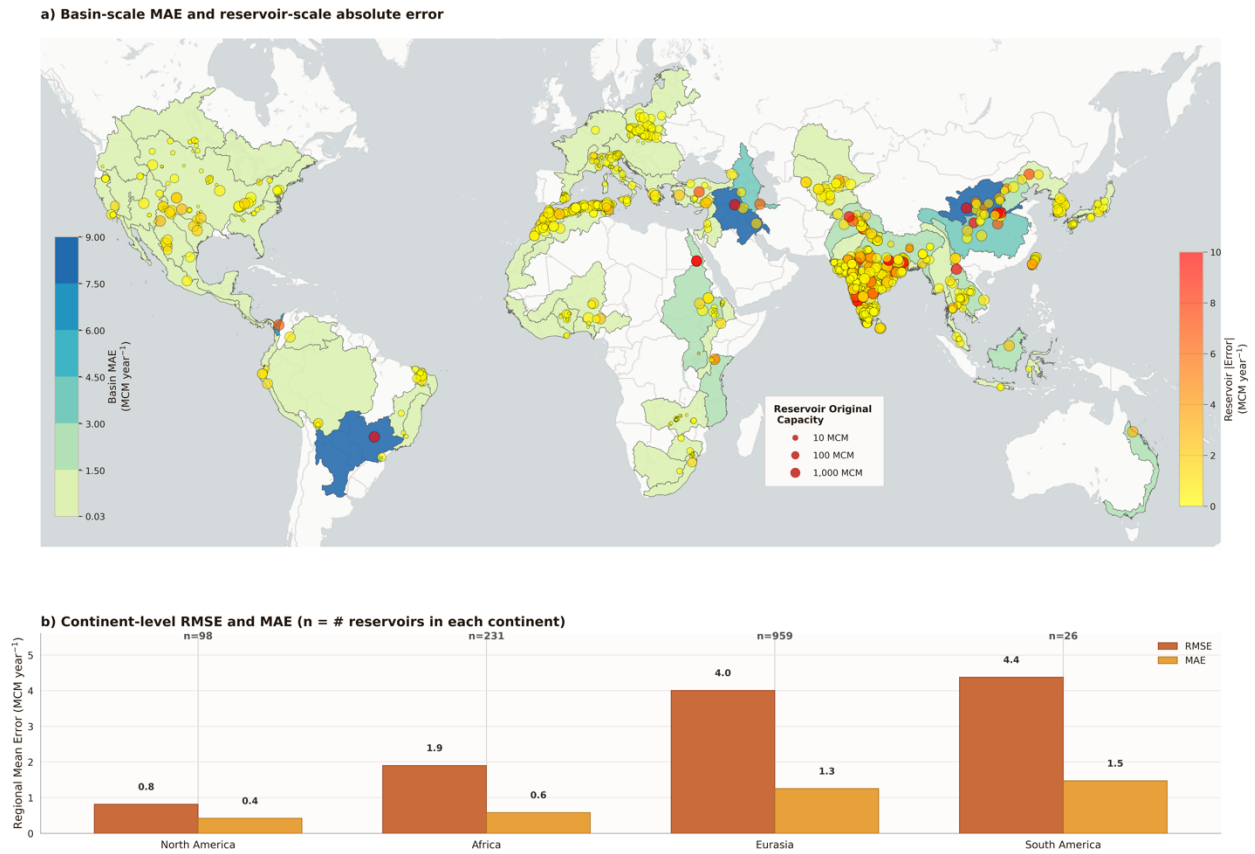


Figure 5.10 Global spatial distribution of RECLAIM in-sample training errors. (a) Basin-scale mean absolute error (MAE, MCM/year) aggregated across major river basins shown by the face color of the basin and reservoir-level absolute prediction error (shown by marker color), with symbol size proportional to individual reservoir storage capacity. (b) Continent-level average of absolute prediction error (MAE) and root mean squared error (RMSE) in MCM/year. Errors reflect in-sample predictions from the final RECLAIM model trained on 100% of the dataset.

Model performance is strongest across North America (RMSE = 0.8 MCM/year, MAE = 0.4 MCM/year; n = 98) and Africa (RMSE = 1.9 MCM/year, MAE = 0.6 MCM/year; n = 231), regions characterized by moderate sedimentation regimes and well-represented training samples. Higher errors are concentrated in Eurasia (RMSE = 4.0 MCM/year, MAE = 1.3 MCM/year; n = 959) and South America (RMSE = 4.4 MCM/year, MAE = 1.5 MCM/year; n = 26), where a small number of large-capacity reservoirs subject to extreme sedimentation rates — located predominantly in the

Indus, Ganges–Brahmaputra, Yangtze, and Yellow River basins, and in Brazil — drive disproportionately large error contributions.

This spatial pattern is consistent with the fold-level variability observed in the cross-validation analysis (Section 5.6.4): the folds with the highest errors (e.g., Split 1 and Split 3) are precisely those drawing disproportionately from high-SR reservoirs in these regions. These results confirm that model difficulties are not arbitrarily distributed but are concentrated in hydro-climatically challenging zones with the most severe global sedimentation loads — an expected pattern rooted in the physical drivers of sedimentation, and one that should guide future data collection priorities and the application of site-specific calibration in Central and South Asia.

5.7. Analysis of Input Drivers of RECLAIM

To evaluate the relative contribution of drivers in predicting reservoir sedimentation and capacity loss, all 88 predictor features described in Section 5.4 were grouped into ten thematic categories. Figure 5.11(a) summarizes the maximum and mean absolute Spearman correlation values (Spearman, 1961) for each category with SR and CLR, while also identifying the specific feature with the strongest correlation in each case.

Table 5.8 Performance evaluation of RECLAIM using dynamic weighting, showing improved robustness across train, validation, and test datasets.

Dats Split	Root Squared Error (RMSE) (in MCM/year)	Mean Error (in MCM/year)	Mean Absolute Error (MAE) (in MCM/year)	Coefficient of Determination (R2)
Train	3.45		1.0	0.95
Validation	3.57		1.15	0.89
Test	4.44		1.65	0.86

Overall, correlation values for CLR are substantially lower across all categories compared to those for SR. This pattern is further illustrated in Figure 5.11(b), which shows the distribution of absolute correlation values. Whereas most features exhibit correlations below 0.2 with CLR, a notable number of features show strong correlations (>0.5) with SR. Interestingly, despite being mathematically related through Equation 5.1, SR and CLR themselves have only a weak correlation ($\rho = 0.24$). This discrepancy helps explain why machine learning models achieved high predictive skill for SR but struggled with CLR: the latter is inherently noisier and less physically tied to individual predictors.

Among individual variables, Original Built Capacity (OBC, Table 5.3) shows the highest correlation with SR, while Relative Capacity to Catchment (ROBC, Table 11.6 in Appendix) is most strongly correlated with CLR. This contrast highlights an important distinction: SR tends to be more closely associated with catchment-scale features, whereas CLR is better explained by normalized metrics that account for storage relative to catchment size.

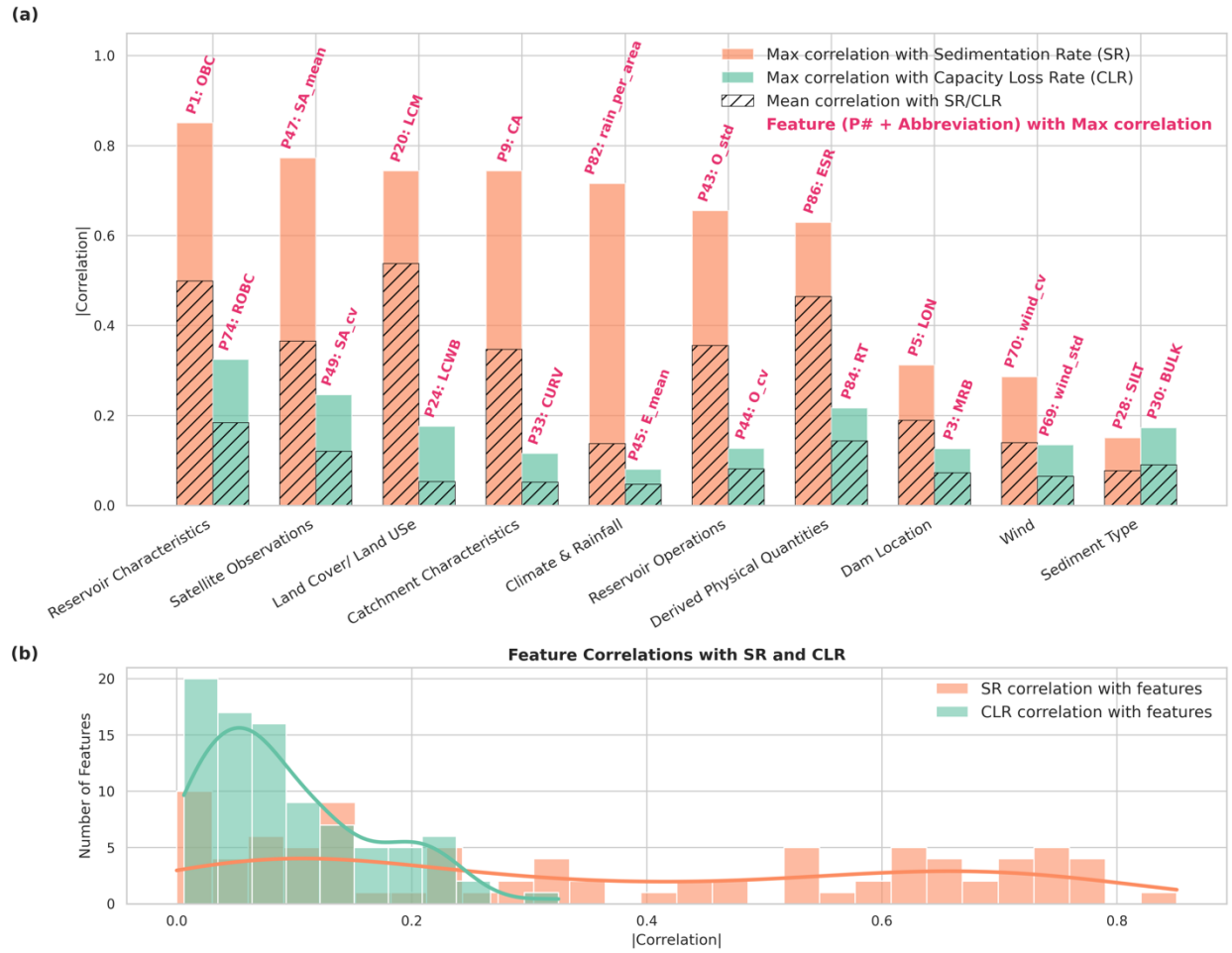


Figure 5.11 **(a)** Maximum and mean absolute correlations of features within each category with sedimentation rate (SR) and capacity loss rate (CLR). The feature exhibiting the maximum correlation in each category is indicated. **(b)** Distribution of absolute correlation values for SR and CLR across all features, with kernel density curves overlaid.

At the category level, land cover and land use variables exhibit the highest mean correlation with SR, whereas reservoir characteristics are most influential for CLR. Climate and rainfall features show minimal relevance for CLR, while sediment type is least important for SR. Satellite-based surface area measures display moderate correlations with both targets. Reservoir operation features derived from satellite-based outflow estimates are also noteworthy: for example, the standard deviation of outflow (O_std, Table 11.5) is most strongly correlated with SR, while the coefficient of variation of outflow (O_cv, Table 11.5) shows the highest correlation with CLR.

Importantly, several categories—such as climate and rainfall, catchment characteristics, and reservoir operations—show a marked drop in maximum correlation values when moving from SR to CLR.

We also assessed the relative importance of all predictor features across the gradient boosting models. For both CLR and SR, regression models were used to compute feature importance. Because individual models can yield substantially different importance rankings, we adopted different ensemble approaches: a simple average for CLR and a weighted average (based on mean model weights used by RECLAIM in the training dataset) for SR.

Figure 5.12 presents feature importance results at the category level, showing both the total summed importance and the most influential individual feature within each category. Original Built Capacity (OBC, Table 5.3) emerged as the dominant predictor for both CLR and SR, although its contribution was more pronounced for SR. At the category level, land cover and land use variables were most important for SR, while static reservoir characteristics dominated for CLR. Within the catchment characteristics category, a single feature tended to drive the signal: catchment aspect (ASP, Table 11.2) for CLR and catchment area for SR. In contrast, derived physical quantities—such as trapping efficiency, residence time, estimated CLR/SR, and sediment fluxes (Table 11.6)—contributed more strongly to CLR than SR. By comparison, sediment type and dam location showed limited influence on either target.

To highlight key drivers at the individual variable level, we further examined the top ten most important predictors from the ensemble models (Table 5.9). While these rankings identify highly influential variables, they can be skewed if a feature receives disproportionate importance in a single model. To address this, we also identified features that consistently held more than 1% importance across all three models (Table 5.10). These “universally important” features represent robust predictors as potential drivers of sedimentation and capacity loss, reducing the influence of outlier model behavior.

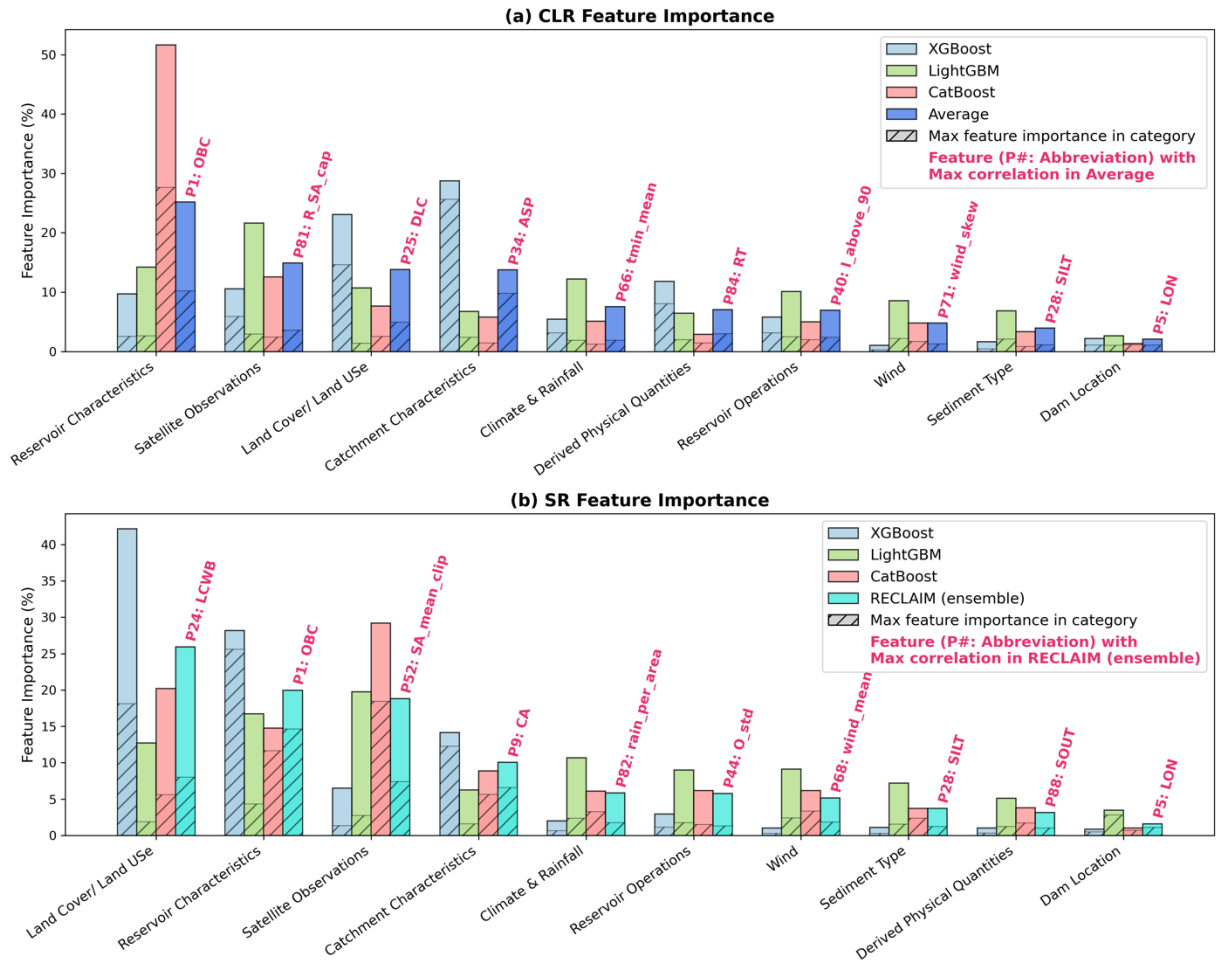


Figure 5.12 Feature importance for predicting capacity loss rate (CLR) and sedimentation rate (SR). **(a)** For CLR, only the total importance of each feature category and the maximum importance within each category are shown for each model. The feature name is indicated only for the “average,” which represents the simple mean of feature importance across the three models. **(b)** For SR, only the total and maximum importance per category are shown for each model. The RECLAIM ensemble displays a weighted average of feature importance across the three models, with weights derived from training data, and the top feature is indicated only for the RECLAIM ensemble.

Taken together, Table 5.9 and Table 5.10 emphasize both commonalities and contrasts between CLR and SR. Original built capacity consistently dominates across metrics, confirming its fundamental role in determining both loss and sedimentation rates. Beyond this, SR relies more

heavily on land cover–based features (e.g., water bodies, cropland, grasslands) and variables associated with sediment transport, such as rainfall and wind. In contrast, CLR is more strongly affected by structural, hydrologic, and environmental conditions, including dam age, trapping efficiency, inflow and outflow variability, and thermal regime. These distinctions suggest that while reservoir size provides the baseline signal, the drivers of CLR and SR diverge—reflecting the balance between catchment processes shaping sediment supply and reservoir-specific characteristics controlling sediment trapping and capacity change.

To further quantify the robustness of RECLAIM to incomplete input data, we conducted a leave-one-feature-out sensitivity analysis using the final ensemble model. Figure 5.13 summarizes the resulting performance degradation in physical terms (ΔRMSE and ΔMAE , in MCM/year), both aggregated by predictor category and for the most influential individual predictors. At the category level, reservoir characteristics and climate-related variables exhibit the highest average sensitivity, whereas categories such as sediment type, derived physical quantities, and reservoir operations show minimal impact when one individual predictor within them is omitted (Figure 5.13(a)). Importantly, this aggregation reflects the distribution of feature-level sensitivities within each category, rather than removal of entire feature groups.

At the individual predictor level (Figure 5.13(b)), original built capacity (OBC) emerges as the most influential variable, with omission leading to a substantial degradation in predictive performance ($\Delta\text{RMSE} \approx 3.64$ MCM/year). Rainfall-related variables, particularly rainfall per unit area, also show strong influence, reflecting the role of catchment-scale hydrological forcing in driving sediment supply. However, beyond a small set of dominant predictors, most features contribute relatively modest degradation (<1 MCM/year), and median changes in predicted sedimentation remain low across reservoirs (Table 11.10 in Appendix). This indicates that RECLAIM does not rely excessively on any single input variable and maintains stable predictive skill even when certain predictors are unavailable, reinforcing its suitability for application in data-limited and globally distributed settings.

Table 5.9 Top ten most important features in ensembled (average models) for both sedimentation rate (SR) and capacity loss rate (CLR).

Rank	SR		CLR	
	Number	Brief description	Number	Brief description
1	P1	Original built capacity	P1	Original built capacity
2	P24	Land cover of water bodies	P34	Catchment aspect
3	P52	Mean surface area in observed timeframe	P74	Relative capacity to catchment
4	P9	Catchment area	P25	Dominant land cover
5	P20	Land cover of mangroves	P73	Age of dam
6	P16	Land cover of grassland	P81	Relative observed surface area to original capacity
7	P23	Land cover of snow and glaciers	P84	Residence time
8	P48	Standard deviation in surface area	P40	Days with inflow above 90 th percentile
9	P68	Mean wind speed	P66	Minimum temperature
10	P82	Rain per unit area	P83	Trapping Efficiency

Table 5.10 Predictor features with more than 1% importance in all three gradient boosting models for both sedimentation rate (SR) and capacity loss rate (CLR).

Rank	SR		CLR	
	Number	Brief description	Number	Brief description
1	P1	Original built capacity	P1	Original built capacity
2	P24	Land cover water bodies	P34	Catchment aspect
3	P48	Standard deviation in surface area	P74	Relative capacity to catchment
4	P15	Land cover of cropland	P73	Age of dam
5	P43	Standard deviation in outflow	P81	Relative observed surface area to original capacity
6	-	-	P40	Days with inflow above 90 th percentile
7	-	-	P66	Minimum temperature
8	-	-	P83	Trapping efficiency
9	-	-	P5	Longitude

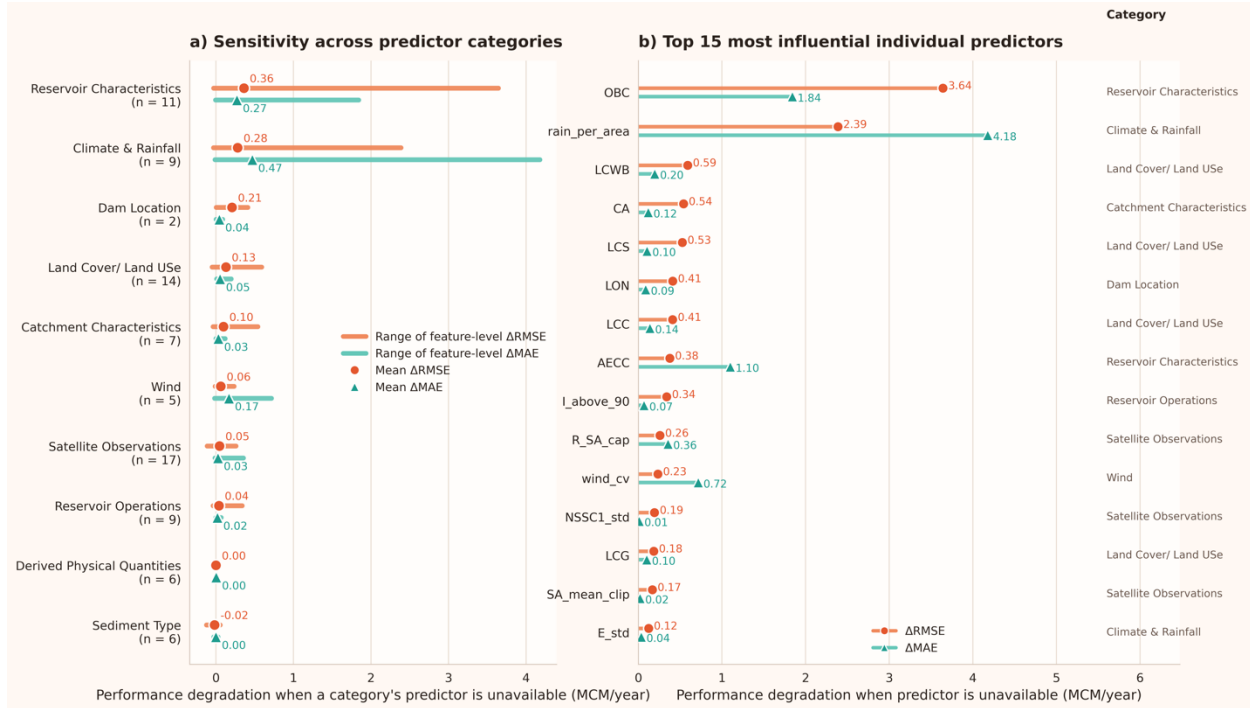


Figure 5.13 Sensitivity of RECLAIM predictions to the removal of individual predictors. Each predictor is omitted one at a time, and the resulting performance degradation is quantified using $\Delta RMSE$ and ΔMAE (MCM/year). (a) Predictor categories showing the distribution (mean and range) of performance degradation across features within each category. (b) Top 15 most influential individual predictors ranked by $\Delta RMSE$.

5.8. Discussion

Reservoir sedimentation is a critical process that undermines water storage capacity, yet predicting it reliably and cost-effectively across diverse global reservoirs has remained challenging until now. Leveraging a dataset of 1,315 reservoirs with 88 predictor features spanning catchment characteristics, land cover, climatic variables, and reservoir-specific attributes, we systematically explored the drivers of sedimentation and capacity loss. Satellite-based observations, particularly surface area measurements, provided key dynamic information that proved more informative than normalized suspended sediment concentration (NSSC) for both sedimentation rate (SR) and capacity loss rate (CLR). Surface area-derived variables likely reflect integrative controls related to reservoir geometry, residence time, and operational variability. Temporal fluctuations in surface area may also indicate storage dynamics (e.g., seasonal drawdown and refill cycles), which

influence sediment settling and retention. In contrast, NSSC primarily represents sediment supply and may not fully capture in-reservoir deposition processes.

Importantly, while RECLAIM leverages 88 predictor features during training, its gradient boosting framework remains scalable in practice because predictions can still be made with only the most influential variables, and users are not required to provide the full set. Feature engineering and transformations are also automated within RECLAIM, reducing the data preparation burden for end-users. These key features of RECLAIM ensure the global scalability and useability of the tool for any reservoir.

A central lesson learned in this study is the limitation of CLR as a predictand for scalable and efficient estimation using ML methods. Despite being derived directly from SR, CLR exhibits low correlation not only with predictor features but even with SR itself (Spearman correlation ~ 0.24). The inability of alternative loss functions to improve CLR regression performance further suggests that its limited predictability is intrinsic to the metric itself. This arises because normalizing sedimentation by reservoir capacity suppresses the influence of catchment-driven sediment inputs, making CLR largely dependent on reservoir-specific characteristics, particularly the original built capacity and its ratio to catchment area.

The role of capacity is further underscored in Figure 5.14, which shows that only the Severe class is associated with distinctly small reservoirs, whereas the other classes span similar capacity ranges. This also explains the high performance of Severe class in classification models. Additionally, CLR values are highly concentrated, with 90% of observed values below 2% per year. In practical terms, small absolute errors in CLR predictions can drastically misrepresent reservoir's remaining lifespan: for example, predicting 1% per year instead of 0.8% per year CLR could suggest a remaining lifespan of 21 years when the actual remaining capacity may be only 1 year, assuming the reservoir age is 79 years.

RECLAIM addresses these limitations by predicting absolute SR using a weighted ensemble of CatBoost, XGBoost, and LightGBM, with dynamic weighting calibrated to sedimentation ranges. The ensemble achieves $\text{RMSE} = 4.44 \text{ MCM/year}$, $\text{MAE} = 1.65 \text{ MCM/year}$, and $R^2 = 0.86$ on the fixed test set, which served as the internal development benchmark during model selection and tuning. To assess generalization to unseen data, a 10-fold group-based cross-validation was conducted, yielding $\text{RMSE} = 7.62 \pm 4.86 \text{ MCM/year}$ and $\text{MAE} = 3.13 \pm 1.66 \text{ MCM/year}$. The cross-validation performance represents the more operationally relevant estimate of generalization for end users, with the variability across folds primarily driven by the skewed, heavy-tailed distribution of sedimentation rates rather than model instability. While absolute errors are larger for high-sedimentation reservoirs, consistent with the skewed distribution of SR across the global dataset, the model reliably identifies and ranks the most severely affected systems, which is the critical capability for water management prioritization and planning.

To contextualize model performance, the mean absolute error from cross-validation ($\text{MAE} = 3.13 \text{ MCM/year}$) provides the more operationally relevant uncertainty estimate for end users. Using the mean reservoir capacity in the dataset ($\sim 1200 \text{ MCM}$) as a representative case, a cross-validation MAE of 3.13 MCM/year corresponds to an uncertainty of approximately 0.26% of capacity per year. Over a 10-year horizon this accumulates to roughly 31 MCM ($\sim 2.6\%$ of capacity), over 20 years to $\sim 63 \text{ MCM}$ ($\sim 5.2\%$), and over a full 50–70 year reservoir lifespan to approximately $157\text{--}219 \text{ MCM}$ ($\sim 13\text{--}18\%$ of capacity).

On an annual basis, this uncertainty ($\sim 0.26\%$ of capacity per year) is small relative to typical sedimentation rates, making RECLAIM well suited for near-term monitoring and operational planning. Over multi-decadal horizons, however, the cumulative uncertainty grows to a range that is physically meaningful for infrastructure planning: a $13\text{--}18\%$ uncertainty in remaining capacity after 50–70 years is consequential when deciding whether to invest in dredging, construct a new reservoir, or decommission an ageing one. RECLAIM is therefore best understood as a triage and prioritization tool, capable of reliably identifying which reservoirs are losing capacity fastest and warrant detailed site-specific investigation, rather than as a substitute for high-resolution in-situ surveys where precise lifespan estimates are required.

Sensitivity analysis further confirms that RECLAIM remains robust under incomplete data conditions, with only a small subset of predictors exerting strong influence on performance while most features contribute marginally.

Feature analysis revealed the contrast between SR and CLR drivers. While original built capacity dominates both, SR is shaped by catchment-scale land cover (water bodies, cropland, grasslands) and sediment transport proxies such as rainfall and wind. CLR depends more on reservoir attributes including dam age, trapping efficiency, and operational variability (inflow/outflow). This distinction underscores the value of domain knowledge in machine learning: aligning the predictand with physical processes (SR) yields more interpretable and transferable models.

While RECLAIM demonstrates strong global performance, the spatial distribution of in-sample training errors reported in Section 5.6.5 provides an initial characterization of regional performance: errors are lowest in North America and Africa, and highest in Eurasia and South America, consistent with the concentration of extreme high-SR reservoirs in those regions. Importantly, because this analysis uses the model trained on 100% of the data, it reflects in-sample fit rather than out-of-sample generalization across regions. Given the current dataset's uneven spatial distribution, true region-specific out-of-sample evaluation remains an important next step; future work will focus on regional assessments and case studies to better characterize spatial variability in predictive skill and to identify where site-specific calibration is most warranted.

Overall, RECLAIM provides a robust, data-driven framework to quantify global reservoir sedimentation, accurately predicting SR while identifying its dominant drivers. Unlike traditional empirical methods that require site-specific calibration, it enables consistent predictions across diverse reservoirs using globally available inputs. By shifting attention from normalized metrics such as CLR to absolute sedimentation rates, and by integrating satellite observations, catchment characteristics, and ensemble learning, RECLAIM enhances the global capacity to monitor and manage reservoir sustainability under increasing sedimentation pressures.

5.9. Conclusion

This work makes three key contributions. First, we show that absolute sedimentation rate (SR) is a more robust predictand metric than capacity loss rate (CLR) in the development of a ML-based method for estimating sedimentation using multi-decadal records of satellite-based Earth observation data. Second, we provide the first global assessment of observed sedimentation drivers from a data-based perspective, highlighting land cover, catchment processes, and satellite-derived surface area as primary determinants of SR, while reservoir operations and structural characteristics dominate CLR. Third, we establish a practical tool for rapid, cost-effective, and scalable sedimentation estimation, enabling informed prioritization of reservoirs for the more expensive in-situ surveys and sediment management strategies.

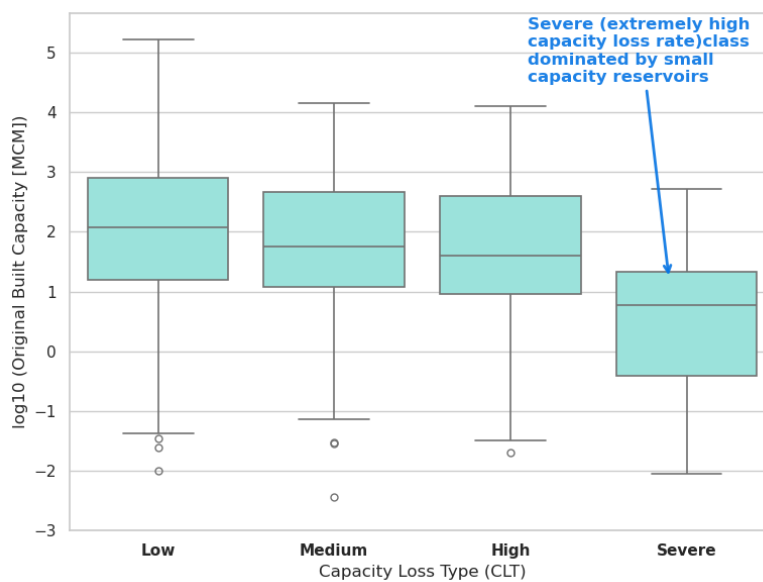


Figure 5.14 Boxplots of log-transformed original built capacity for each of the four capacity loss type (CLT) classes. The Severe class, representing reservoirs with extremely high capacity loss rates, is primarily composed of small-capacity reservoirs.

A point to note here is that the development of a sedimentation estimation tool such as RECLAIM, which we claim as a first of its kind in terms of its global scalability, is premised on the development and validation of two necessary and foundational tool and dataset. These are: 1) the Reservoir Assessment Tool (version 3.0, Minocha et al., 2024) without which it would have

computationally almost unfeasible to track the multidecadal reservoir operation pattern of reservoirs in a distributed manner; and 2) the GRILSS dataset (Minocha and Hossain, 2025a) on reservoir sedimentation that is essential for calibrating and validating any globally scalable tool. Both of these tool and dataset were developed by the authors towards the ultimate goal of developing this first-of-its-kind tool for reservoir sedimentation called RECLAIM that the water community of practitioners and scientists so urgently needs today.

While RECLAIM demonstrates strong global performance, its current training set—reservoirs distributed across 74 major river basins—may introduce slight regional biases toward areas with denser observational coverage. As the community continues to contribute to and expand the GRILSS dataset, the inclusion of additional sedimentation records will further strengthen the model’s stability and applicability across diverse hydrological settings (Minocha and Hossain, 2025a). This represents an opportunity to refine and expand the framework in future iterations. Sensitivity analyses suggest that predictions are primarily governed by catchment-scale physical and climatic characteristics; however, improved geographic coverage will be important to further evaluate and reduce potential regional biases.

In conclusion, our findings demonstrate that sedimentation can be effectively monitored at global scale using existing satellite and observational data with ML methods. RECLAIM provides a rapid, scalable, and cost-effective screening tool, capable of identifying reservoirs potentially at higher risk of diminished storage capacity and guiding where detailed surveys or mitigation interventions are most urgently needed.

With a monitoring platform (RAT), a curated observational archive (GRILSS), and a predictive model (RECLAIM) now in place, the dissertation's cumulative infrastructure is sufficient to ask the central scientific question that motivated the entire enterprise: how fast is the world actually losing reservoir storage, and how are climate variability and long-term change shaping that trajectory? Chapter 6 synthesizes these tools into a global, satellite-era analysis of reservoir sedimentation, revealing regional patterns, temporal trends, and the fingerprint of climate

teleconnections such as ENSO—translating the methodological advances of the preceding chapters into a definitive empirical account of the state of the world's reservoirs.

Chapter 6. Hidden Sediments, Lost Capacity: How Fast Is the World Losing Reservoir Storage in a Changing Climate?

Note: This chapter has been under revision in its current form in *Proceedings of the National Academy of Sciences (PNAS)*. The only differences are in the numbering of figures, tables, and references to other sections.

6.1. Abstract

Reservoir sedimentation progressively reduces global water-storage capacity, yet its magnitude, spatial organization, and climatic controls remain poorly understood at a global scale. Here we present the first multi-decadal assessment of reservoir sedimentation from 1984–2023 derived from Earth observations, integrating machine-learning–based sediment estimation with climate variability across 1,412 societally critical reservoirs worldwide. These analyses form the **Global Long-term Reservoir Sedimentation** dataset (GLoRS), a temporally granular framework for quantifying sediment-driven storage loss at scale. Total installed storage in this dataset is approximately 3,630 km³, of which an estimated 88.4% remains in 2023. Globally, major reservoir storage capacity is declining at an average rate of 0.42% per year due to sedimentation, and the typical large reservoir has already lost nearly one-fifth of its original capacity. Since the 1980s, global mean annual sedimentation rates have increased by approximately 0.43 Million Cubic Meter (MCM) per year every decade. Both monotonic trends and El-Nino Southern Oscillation (ENSO) associations display pronounced geographic clustering, revealing hydroclimatic organization of sediment dynamics. Climate variability primarily amplifies extreme sedimentation events rather than uniformly shifting mean deposition rates. Reservoir-level attribution further identifies inflow variability as the most common natural driver of this variability and shows that human decisions about how a reservoir is operated (outflow release and pool level) explains sedimentation-rate variability more often than natural climatic drivers, in 61.3% of the ~500 large-scale infrastructure reservoirs studied. Together, these findings demonstrate that reservoir sedimentation is neither spatially random nor temporally stationary, with direct implications for the resilience of global water storage systems under intensifying hydroclimatic variability.

6.2. Introduction

Reservoirs created by dams form the basis of modern water, food, and energy systems. Today, more than 62,000 large dams (used interchangeably with reservoirs hereafter) now regulate river flows worldwide, providing irrigation, hydropower, flood control, and urban water supply (ICOLD, 2025). While the global inventory of dams continues to expand, the usable storage they provide does not. Reservoirs lose capacity over time as sediment carried by rivers is trapped behind dams and deposited on the reservoir bed. This process is irreversible at anthropogenic timescales and progressively erodes the benefits reservoirs were designed to deliver (Kondolf et al., 2014 and Wisser et al., 2013).

Despite its importance, the current state of global reservoir storage capacity remains largely unknown. Early global estimates suggest that reservoirs lose approximately 31 km³ of storage annually, equivalent to about 0.52% of total installed capacity (Sumi et al., 2004). At the same time, storage capacity per capita has declined as population growth has outpaced new dam construction. Between 1990 and 2010, the global population increased by 30%, while installed reservoir capacity grew by only 9%, leading to a 19% decline in per-capita storage since its peak in the late 1980s—even under the assumption of no sedimentation (Wisser et al., 2013). Such assessments implicitly assume static or temporally invariant sedimentation rates. Yet sedimentation is neither spatially uniform nor temporally constant.

Sedimentation rates evolve in response to changes in land use, climate, hydrology, and reservoir operations, which can accelerate or decelerate sediment accumulation over time (Hoegh-Guldberg et al., 2018). As a result, estimates based on fixed or historical rates provide little insight into the pace at which storage is being lost today, or which reservoirs are approaching unsustainable thresholds. The consequences of this uncertainty remain largely unrecognized. Declining effective storage reduces water availability for irrigation, hydropower, and domestic use, while simultaneously limiting the ability of reservoirs to mitigate floods and droughts under increasing hydroclimatic variability (Yasarer and Sturm, 2016; Suresh et al., 2024).

Beyond these systemic impacts, sedimentation governs the functional lifespan of a reservoir (Morris and Fan, 1998). Decisions related to infrastructure planning, risk assessment, and sediment management therefore depend critically on how storage capacity evolves through time (George et al., 2017). Yet direct measurements of sediment accumulation rely on bathymetric surveys that are

costly, infrequent, and geographically sparse (Samaila–Ija et al., 2014; Patil et al., 2015). Even in data-rich regions, such surveys cover only a small fraction of existing reservoirs, leaving the vast majority unmonitored (Gray et al., 2010; Central Water Commission, 2020).

Remote sensing and numerical modeling offer partial alternatives, but both face critical limitations at global scale. Numerical models require detailed in-situ inputs that are rarely available, while satellite-based approaches often depend on long records of coincident water level and surface area observations that are inconsistent across space and time (Ghosh et al., 2024; de Oliveira Fagundes et al., 2020; Dutta, 2016). As a result, existing approaches have been insufficient to provide a global, time-resolved view of reservoir sedimentation (Gonzalez et al., 2023; Wisser et al., 2013; Perera et al., 2023).

To address this gap, we apply the recently developed and tested tool called RECLAIM (**R**eservoir **E**stimation of **C**apacity **L**oss using **AI** based **M**ethods) framework (Minocha et al., 2025a, see Sections 2-3 for details) as a unified global assessment. RECLAIM integrates multi-decadal satellite Earth observations with curated in-situ sediment records and basin-scale hydroclimatic and geomorphic predictors to estimate reservoir sedimentation. Using this framework, we reconstruct annual sedimentation rates from 1984–2023 without reliance on repeated bathymetric surveys.

Applying this approach to 1,412 reservoirs spanning 75 major river basins (Figure 6.1), we provide the first observationally constrained, multi-decadal assessment of global reservoir capacity change from 1984–2023. Our analysis quantifies how much storage remains, the pace at which it is being lost, and how sedimentation rates have evolved over time. Beyond cumulative capacity loss, we resolve the spatial organization, temporal variability, and climate sensitivity of sedimentation dynamics at planetary scale. The resulting Global Long-term Reservoir Sedimentation dataset (GLoRS v1.0; Minocha & Hossain, 2026) provides a global foundation for reassessing dam infrastructure reliability, prioritizing reservoirs most vulnerable to capacity decline, and evaluating how climate variability reorganizes sediment transport in regulated river systems.

This study's contribution spans two distinct layers. RECLAIM (Minocha et al., 2026) and GRILSS (Minocha and Hossain, 2026), the machine-learning framework and training dataset underlying our sedimentation estimates, are prior methodological work that makes the present study possible; they are not themselves presented as new contributions here. The scientific novelty of this study

is GLoRS v1.0 itself: the first global, annual-resolution, multi-decadal (1984-2023) dataset of reservoir sedimentation dynamics across 1,412 reservoirs, and the population-level statistical and mechanistic analyses it enables, including the geographic organization of sedimentation trends and ENSO teleconnections, and the reservoir-level attribution of sedimentation-rate variability to specific natural climatic and reservoir-operations drivers, none of which could be conducted from the underlying reservoir-scale tools alone.

6.3. Data

A total of 1,412 reservoirs distributed across 75 major river basins and 82 countries were included in this study. Of these, 1,012 reservoirs were selected from the Global Reservoir Inventory of Lost Storage by Sedimentation (GRILSS; Minocha & Hossain, 2025b). The remaining 400 reservoirs correspond to the largest dams in the Global Reservoir and Dam database (GRanD; Lehner et al., 2011) that are not included in GRILSS. These GRanD reservoirs represent a substantial fraction of global installed storage capacity (approximately 3,000 km³) and represent some of the world's most societally critical large-scale surface water storage infrastructures.

As introduced earlier, reservoir sedimentation was estimated using RECLAIM (Reservoir Estimation of Capacity Loss using AI-based Methods) framework. This is a data-driven machine learning model that predicts annual sedimentation rates from a combination of static reservoir and catchment characteristics (e.g., design capacity, dam height) and time-varying drivers, including reservoir operations and catchment-scale hydroclimatic conditions (Table 12.1). RECLAIM was trained and validated using the GRILSS dataset in a prior work (Minocha et al., 2025a), which provided historical sedimentation observations and associated attributes for model development. In evaluation on an independent held-out test set, RECLAIM achieved a prediction RMSE of 4.44 Million Cubic Meter (MCM) per year (yr⁻¹), Mean Absolute Error (MAE) of 1.65 MCM yr⁻¹, and R² of 0.86. A 10-fold group-based cross-validation, with reservoir independence enforced across folds, gives RMSE = 7.62 ± 4.86 MCM yr⁻¹ and MAE = 3.13 ± 1.66 MCM yr⁻¹, representing generalization to unseen reservoirs (Minocha et al., 2026). The fixed held-out test-set metrics represent the internal development benchmark used during model selection and tuning, whereas the group-based cross-validation provides the operationally relevant assessment of generalization to unseen reservoirs (Minocha et al., 2026). Model performance is strongest for large reservoirs (>1 km³), while relative error increases for smaller reservoirs, particularly below 1 MCM, as

detailed in Appendix Section 12.1, which contextualizes these performance and uncertainty assessments for the present study.

We introduce the **Global Long-term Reservoir Sedimentation** dataset (GLoRS v1.0), the first global dataset providing 40 years (1984–2023) of annual sedimentation time series for more than 1,400 reservoirs. The dataset is released as an open-source product to facilitate broader scientific application and reproducibility.

Importantly, RECLAIM does not use time or year as an explicit predictor; temporal dynamics are instead encoded through dynamic features—satellite-derived surface metrics, precipitation anomalies, and catchment climate—that vary from year to year and describe the state of each reservoir's catchment at a given time. The reported R^2 is computed by comparing predicted against survey-observed sedimentation across reservoirs, with each reservoir's dynamic features constructed from the specific time frame spanned by its own survey record. A reservoir surveyed in 2004–2005 therefore contributes features drawn from 2004–2005, whereas one surveyed in 2014 and 2018 contributes features drawn from 2014–2018. The metric consequently integrates across-reservoir (spatial) and across-survey-period (temporal) variation simultaneously and does not represent a purely spatial fit.

RECLAIM requires reservoir-level attributes including design storage capacity, dam height, year of construction, geographic location (latitude and longitude), and associated reservoir and catchment geometries (Table 12.1). These attributes, except for catchment boundaries, are available for all GRILSS reservoirs and for the selected GRanD reservoirs. GRILSS additionally provides catchment polygons for nearly all reservoirs, whereas GRanD does not include catchment boundaries. For GRanD reservoirs, contributing catchments were delineated using the Watershed tool in ArcGIS Pro, based on a 90 m digital elevation model, following a methodology consistent with the catchment delineation approach used for GRILSS (Minocha & Hossain, 2025b).

Differential catchment area (DCA) was computed by integrating reservoir locations with the high-resolution (15-arc-second) HydroSHEDS flow-direction dataset (Lehner et al., 2008) and the ResORR (Reservoir Operations-driven River Regulation) network algorithm (Das et al., 2024; Minocha et al., 2024b). This procedure identifies immediately upstream reservoirs and subtracts their contributing drainage areas from that of the focal reservoir.

Time-varying inputs required by RECLAIM (rows 11–20, Table 12.1) were obtained using the Reservoir Assessment Tool (RAT 3.0; Minocha et al., 2024a), a satellite-based reservoir monitoring framework available as an open-source Python library (Minocha et al., 2025d). The satellite and reanalysis data products used by RAT to generate these time series are summarized in Appendix, Table 12.2. In addition to time-varying inputs, RAT also provides reservoir bathymetry in the form of an area–elevation curve (AEC).

RECLAIM is therefore not a remote-sensing retrieval algorithm. Predictive skill derives from the joint behavior of many physical drivers rather than any single observational input. Two of these, NSSC1 and NSSC2, are surface-reflectance band-ratio proxies for suspended sediment concentration (near-infrared/Red and Red/Green, respectively) and cannot directly resolve bedload transport or subsurface density currents. They account for only two of RECLAIM's twenty raw inputs and roughly ten of its eighty-eight engineered features. The rest span reservoir geometry, catchment characteristics, hydrology, and climate. This surface-layer limitation is addressed further in Appendix Section 12.2.

6.4. Methods

6.4.1. Observation period and aggregation

For each reservoir in GLoRS, the observation period spans from 1984—or the year of dam construction, if later—through 2023. The year 1984 was selected to coincide with the onset of consistent global satellite data availability. RECLAIM was applied to generate annual time series of sedimentation rates for each reservoir over its observation period using the pretrained ensembled model. RECLAIM, distributed as an open-source Python package, internally handles feature generation by deriving more than 80 engineered features from the input variables listed in Table 12.1 (in Appendix) to produce annual sedimentation estimates. In this study, all inputs listed in Table 12.1 were supplied for all reservoirs, except for a few small dry dams from GRILSS where reservoir shapefiles were unavailable. To ensure consistency and reliability, GLoRS includes only reservoirs within major river basins on which RECLAIM was trained.

Time series of annual storage capacity loss (expressed as a percentage) were derived using Equation (1). These annual rates were further aggregated to estimate total sediment volume deposited (MCM) and cumulative capacity loss (%) over the observation period. For pre-1984

periods, sedimentation was assumed to vary linearly from the year of construction to 1984, and no active dredging or sediment management was considered for aggregating purposes. This linear treatment is a practical necessity rather than a physical claim: no consistent global satellite record exists before 1984, so some form of extrapolation is unavoidable for reservoirs impounded earlier. It does not represent the non-linear decline in trap efficiency expected as a reservoir fills, nor the concentration of sediment delivery into individual extreme hydrological years. We note that a globally consistent, annually resolved reconstruction of reservoir sedimentation was not feasible at all prior to the convergence of multi-decadal Earth observation archives, cloud-based processing, and automated reservoir monitoring; extending such records further back in time will require a sedimentation reanalysis analogous to those now routine for meteorological variables.

$$\text{Capacity Loss Rate} = \frac{\text{Sedimentation Rate}}{\text{Original Built Capacity}} * 100 \quad (1)$$

For reservoirs where the aggregated sediment volume exceeded design capacity, the volume was capped at the design capacity, as sediment accumulation cannot physically surpass the reservoir's original storage volume. Consequently, TFCL values approaching 100% reflect modeled cumulative impact under the above stated simplifying assumptions rather than confirmed operational failure.

This cap is one consequence of a more general structural property of the framework: RECLAIM predicts annual sedimentation rates from observations in the year being predicted rather than tracking cumulative sediment state, so it does not represent the trap-efficiency decline described by Brune's curve. Annual rates for reservoirs in advanced stages of filling are consequently likely to be overestimated, and the design-capacity cap functions as an external safeguard against physically impossible cumulative states rather than a representation of that decline. This defined scope limitation is addressed further in Appendix Section 12.3.

The same absence of state memory means that capacity recovered through dredging or sediment flushing is not represented in GLoRS v1.0. However, because active sediment management alters

physical covariates such as land cover and upstream sediment supply, RECLAIM's predictions may partly reflect management activity in basins where it is intensive, even though management status is not an explicit model input. This possible contributing factor is addressed further in Appendix Section 12.3.

6.4.2. Definition of Sedimentation and Capacity Metrics

Sedimentation impacts were characterized using four primary metrics:

- (i) Sedimentation Rate (SR) (MCM yr^{-1}),
- (ii) Capacity Loss Rate (CLR) ($\% \text{ yr}^{-1}$),
- (iii) Total Sedimentation Amount (TSA) (MCM), and
- (iv) Total Fractional Capacity Loss (TFCL) (%).

SR represents the annual volume of sediment deposited within a reservoir. CLR denotes the corresponding annual percentage reduction in design storage capacity. TSA quantifies the cumulative sediment volume deposited over a specified period, while TFCL expresses cumulative storage loss as a percentage of the original design capacity. Together, these metrics distinguish between volumetric sediment accumulation and relative depletion of storage capacity, enabling consistent comparison across reservoirs of different sizes and operational significance.

6.4.3. Reservoir subset for large-scale infrastructure analysis

In addition to the full sample of 1,412 reservoirs from GLoRS, representing 3,630.62 km³ of installed storage capacity, a subset of reservoirs with original design capacity greater than 1 km³ (1,000 MCM) was identified to address societally-critical infrastructure. This threshold yielded 500 reservoirs across 61 major river basins and 65 countries, collectively accounting for approximately 3,528.57 km³ of storage. These reservoirs comprise a substantial fraction of global regulated surface water storage—approximately 44% of the estimated 8,110 km³ of total global reservoir capacity reported by Lehner et al. (2024).

GLoRS deliberately restricts its scope to large reservoirs rather than attempting comprehensive coverage of every dam-scale water body catalogued in databases such as GeoDAR (Wang et al., 2022), which includes very large numbers of small dams below the threshold relevant to global

storage accounting. This is a scope decision grounded in scientific priority rather than an oversight: large reservoirs (design capacity greater than 1 km³) account for most of the global installed storage capacity, so their capacity-loss trajectory is the policy-relevant quantity for global water-security assessment, and their exclusion of smaller dams does not materially affect the global capacity-loss estimates emphasized here. We acknowledge that GLoRS may not capture every large dam worldwide, which could introduce a minor geographic bias in global estimates, and note extending coverage toward smaller, more numerous reservoirs as a priority for future dataset versions.

Owing to their scale and strategic importance, these large reservoirs sustain regional and national economies by supporting hydropower generation, irrigated agriculture, municipal and industrial water supply, and flood attenuation for densely populated downstream areas. Many of these systems regulate major river basins and buffer hydroclimatic extremes, thereby safeguarding millions of people from flood and drought risks. Any sustained loss of effective storage in these reservoirs therefore has societal implications that extend far beyond local catchments, influencing energy security, food production, and climate resilience at regional or continental scales.

While global patterns were evaluated across the complete set of reservoirs, detailed analyses of sedimentation dynamics and temporal trends were conducted primarily on this subset to assess risks to the world's most consequential water infrastructure systems.

6.4.4. Temporal Variation and Trend Analysis

6.4.4.1. Regional Variability Metrics

To quantify regional differences in sedimentation variability, dispersion metrics were computed for the subset of large reservoirs. Analyses were performed at both continental and Köppen–Geiger climate-zone scales. Each reservoir was assigned to one of four major Köppen–Geiger climate categories (Beck et al., 2023)—tropical, temperate, arid, or cold—based on its geographic location (Figure 6.1). This classification was used to compute climate-zone–level statistics in Section 6.5.

Spatial variability was defined as the interquartile range (IQR) of long-term mean sedimentation rates (SR) across reservoirs within each region, capturing cross-reservoir heterogeneity. Temporal variability was defined as the IQR of annual regional mean SR over 1984–2023, representing

interannual fluctuations in sedimentation intensity. Median SR over the full study period was also calculated for each region to characterize central tendency.

6.4.4.2. Climate Variability Response (ENSO)

To assess the influence of large-scale climate variability on reservoir sedimentation, we analyzed the response of annual sedimentation rate (SR) anomalies to the El Niño–Southern Oscillation (ENSO).

ENSO variability was represented using sea surface temperature (SST) anomalies in the Niño 3.4 region, obtained from the NOAA Climate Prediction Center (CPC) SST index dataset. For each reservoir, SR anomalies were calculated relative to the long-term mean sedimentation rate. Pearson correlation coefficients were then computed between the Niño 3.4 SST anomaly time series and the SR anomaly time series.

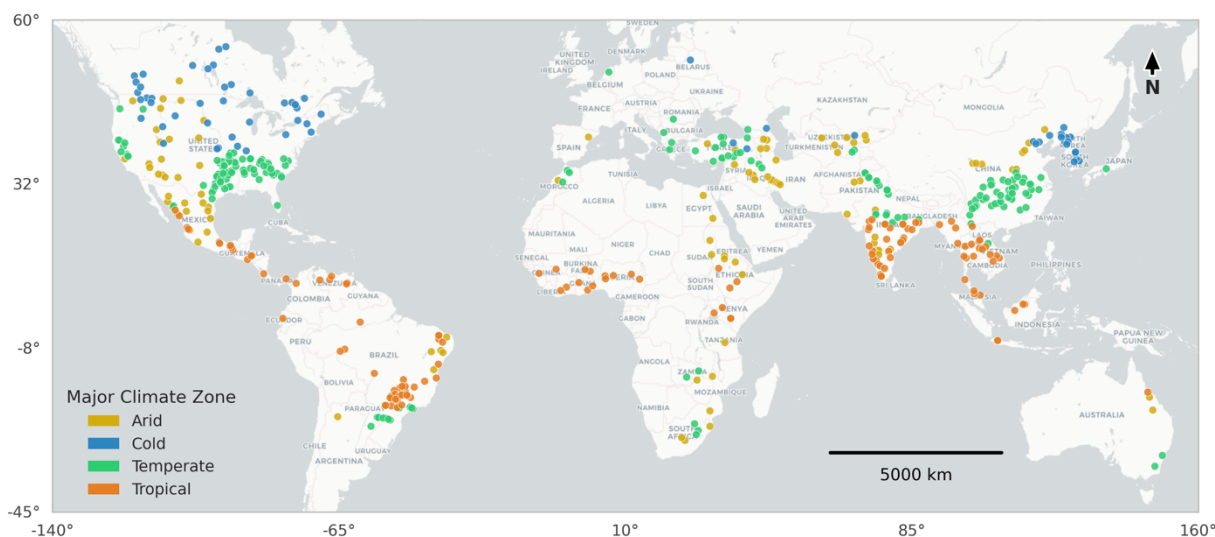


Figure 6.1 Global geospatial distribution of 1,412 reservoirs in the GLoRS dataset, classified into four major Köppen–Geiger climate categories.

Positive correlations indicate enhanced sedimentation during El Niño phases (positive SST anomalies), while negative correlations indicate enhanced sedimentation during La Niña phases (negative SST anomalies). Based on these correlations, reservoirs were classified as El Niño–dominated or La Niña–dominated according to the phases during which their sedimentation was most pronounced.

Because ENSO teleconnections act on tail events rather than shifting the annual mean, and because any single reservoir's sedimentation-rate record is too short to establish an individual correlation as robust on its own, we tested robustness at the population level using three complementary tests: a moving-block bootstrap (Künsch, 1989) comparing cross-reservoir composite mean and extreme sedimentation-rate anomaly curves against Niño 3.4 SST anomalies, a null-permutation test against randomly drawn reservoir groups, and a sensitivity check across alternative classification thresholds ($|r| \geq 0.10$ to 0.30). Full methodological detail, including bootstrap parameters, resampling counts, and threshold results, is provided in Appendix Section 12.4.

6.4.4.3. Long-Term Trend Detection

Long-term monotonic trends in annual sedimentation rates were evaluated using the Mann–Kendall (MK) test (Mann, 1945; Kendall, 1975) in conjunction with the Theil–Sen slope estimator (Sen, 1968). The MK test is widely applied in hydrological and climatic time series analyses to detect persistent monotonic trends (Khan et al., 2021; Minocha et al., 2024c; Sang et al., 2014). To account for variance inflation due to serial autocorrelation, the Yue and Wang modified MK test was employed (Yue and Wang, 2004). Statistical significance was assessed at the 0.05 level. Reservoirs exhibiting significant trends were classified as increasing or decreasing based on the sign of the Sen's slope.

6.4.4.4. Mechanistic Drivers of Climate–Sedimentation Linkages

To identify which physical pathways transmit sedimentation-rate variability, we tested the direct relationship between each reservoir's sedimentation-rate anomaly and seven candidate natural (“delivery”) drivers spanning four mechanism categories — hydroclimatic forcing (precipitation, wind speed), hydrologic transport (reservoir inflow), atmospheric extremes (frequency, intensity, and extreme precipitation of Atmospheric Rivers, from the PIKART catalog (Vallejo–Bernal et al., 2025)), and landscape disturbance (MODIS-derived wildfire burned-area fraction (Giglio et al., 2021)) — together with two reservoir-operations (“retention”) variables (outflow, surface area/pool level) reflecting sediment trapping efficiency rather than delivery from the catchment.

We refer to these two variables collectively as reservoir-operations drivers throughout — since they reflect direct operator control over release and pool level — as distinct from the natural

climatic drivers that govern sediment delivery from the catchment; this operations/climate distinction denotes the mechanism through which each driver acts, not a claim that reservoir management processes are entirely free of climate influence. For each reservoir we computed autocorrelation-corrected correlations (effective sample size; Bretherton et al., 1999) at zero- and one-year lag, retaining the stronger relationship, and applied a per-category Šidák correction (Šidák, 1967) so that mechanism categories with more candidate variables were not favored merely by having more opportunities to show a large correlation by chance. Full methodological detail, including data sources for candidate variables, is provided in Appendix Section 12.5.

6.4.5. Process-Based Case Study Analysis

To complement the global statistical assessment, a small number of representative reservoirs were analyzed to evaluate whether RECLAIM-derived sedimentation time series can yield physically interpretable sediment regime shifts associated with documented geomorphic or infrastructural disturbances. For each case study reservoir, annual sedimentation rates were segmented into pre-disturbance and post-disturbance periods based on known event years (e.g., major earthquake or dam commissioning).

To quantify the magnitude of regime shifts, differences in mean sedimentation rate between periods were normalized by the pooled standard deviation using Cohen's d (Cohen, 2013). This standardized effect size enables comparison of shifts relative to natural interannual variability. These analyses were intended as mechanistic validation examples rather than as components of the global statistical inference.

6.5. Results

6.5.1. Global Patterns in Reservoir Sedimentation

GLoRS quantifies cumulative sediment deposition and associated storage loss for 1,412 reservoirs worldwide through 2023, reporting total sedimentation amount (TSA; MCM) and total fractional capacity loss (TFCL; %). Figure 6.2 maps these metrics globally (TSA in panel a; TFCL in panel b) and reveals strong spatial contrasts. In several regions (like Northern Africa, Europe and South Asia), TFCL is high despite modest TSA, consistent with smaller reservoirs undergoing rapid proportional depletion, whereas other regions (like Middle-East and parts of Canada), show high

TSA but low TFCL, reflecting large-capacity systems where substantial volumetric deposition translates to limited relative loss.

These patterns are further clarified in Figure 6.2c, which relates TSA to TFCL and colors reservoirs by original design capacity. A clear size-dependent pattern emerges: smaller reservoirs can experience high TFCL even at moderate TSA, while larger reservoirs accumulate greater sediment volumes while maintaining lower proportional depletion. This divergence underscores the importance of evaluating both absolute (MCM) and normalized (%) sedimentation measures when assessing storage vulnerability. TFCL values approaching 100% reflect modeled cumulative impact under simplifying assumptions (Section 6.4.1) and should be interpreted as severe sedimentation impact rather than literal storage exhaustion.

To assess system-level patterns, we aggregated installed storage and estimated remaining capacity in 2023 at continental and climate-zone scales (Figure 6.3). Marked regional contrasts emerge. Australia exhibits the highest estimated proportional capacity loss (~24%) but represents a small installed storage base (~12 km³), whereas North America shows high proportional loss (~16.8%) despite substantial installed capacity. Eurasia contains the largest installed capacity (~1,264 km³) and still exhibits relatively high proportional loss (~13.9%), while Africa, with the second-largest installed capacity (~960 km³), shows the lowest proportional loss (~4.9%).

Climate-zone aggregation reveals a comparable structure. Cold regions exhibit the highest estimated proportional loss (~15.4%), followed by temperate (~13.1%) and arid (~12.7%) regions, whereas tropical regions—despite holding the largest installed capacity (~1,292 km³)—show the lowest proportional loss (~8.6%). Together, these results indicate that proportional loss does not scale monotonically with installed capacity and that aggregated vulnerability depends jointly on storage scale and sedimentation intensity.

Figure 6.4 further contextualizes these findings by ordering reservoirs by decreasing design capacity and plotting cumulative installed and remaining capacity. Across all 1,412 reservoirs, installed capacity totals ~3,630 km³, of which ~88.4% remains in 2023. Restricting the analysis to reservoirs larger than 1 km³ yields ~3,529 km³ installed capacity with ~89% remaining. Because these nearly identical remaining-capacity fractions apply to almost the same total installed storage,

most absolute storage loss in GLoRS is concentrated within the large-reservoir subset. This motivates the focused analysis of these societally-critical reservoirs in the following sections.

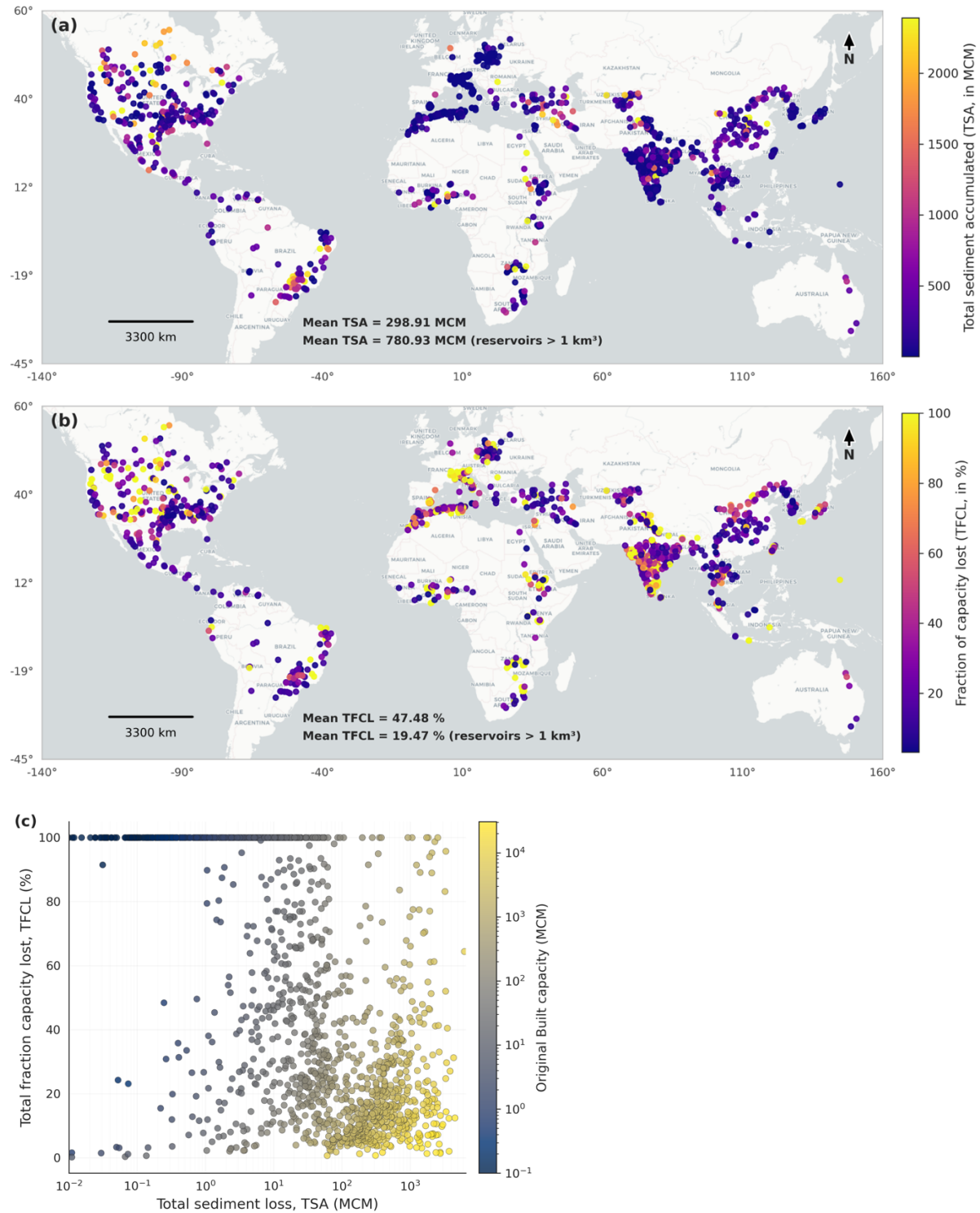


Figure 6.2 Global cumulative sedimentation and associated proportional storage loss in GLoRS through 2023. (a) Total sedimentation amount (TSA; MCM). (b) Total fractional capacity loss (TFCL; %). (c) Relationship between TSA and TFCL, colored by original design capacity.

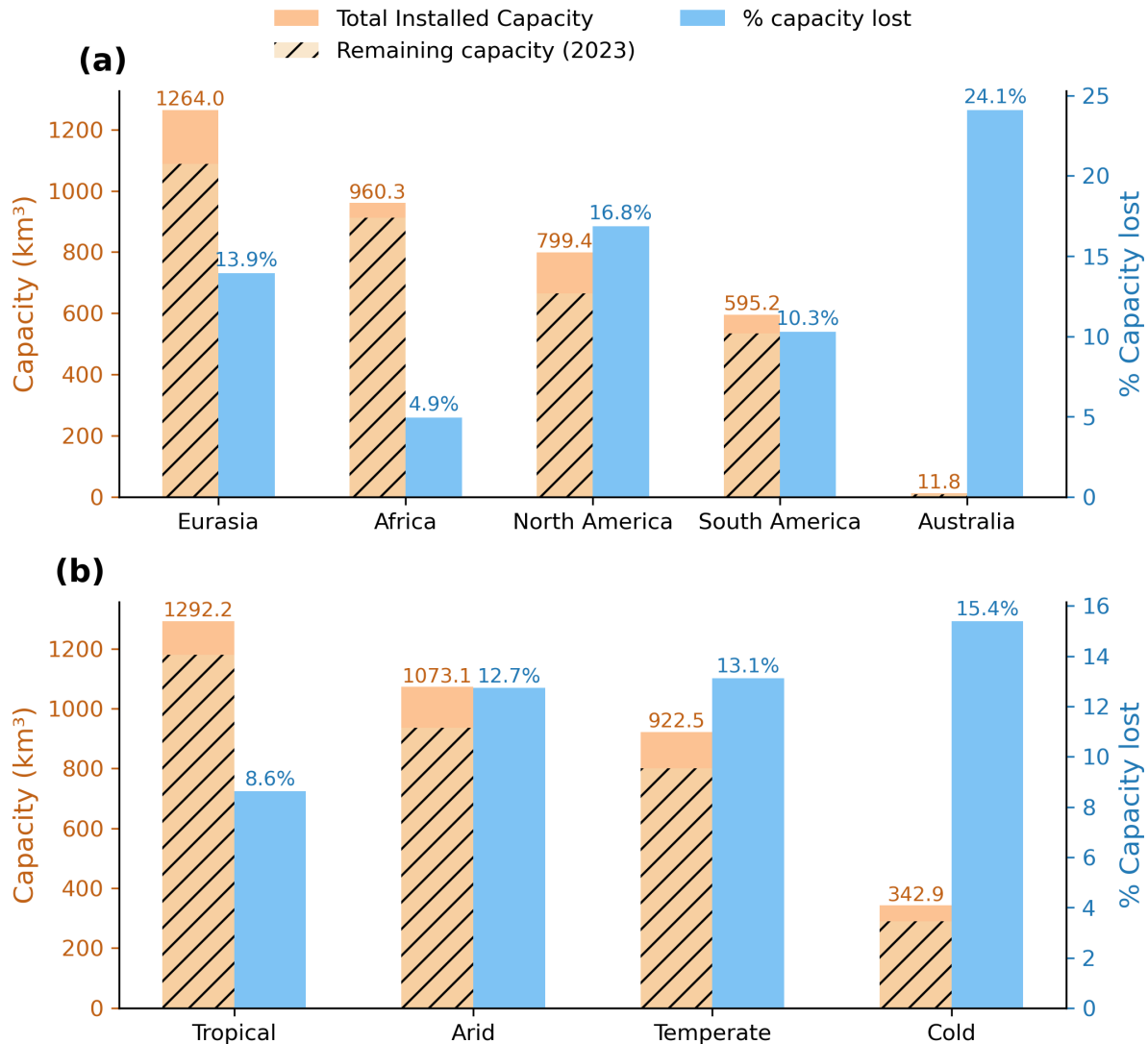


Figure 6.3 Installed storage capacity and proportional loss across regions. (a) Continental totals and (b) Köppen–Geiger climate-zone totals showing original installed capacity, remaining capacity in 2023 (hatched bars), and proportional storage loss (blue bars) considering all reservoirs in GLoRS.

6.5.2. Sedimentation in Critical Large-Scale Reservoir Infrastructure

Figure 6.5 presents the spatial distribution of long-term mean sedimentation rate (SR) and corresponding mean annual capacity loss rate (CLR) for reservoirs with original design capacity $>1 \text{ km}^3$, representing the world's major water-storage infrastructure. Marker size denotes installed storage capacity, enabling direct comparison between infrastructure scale and sedimentation metrics.

Across these large reservoirs, storage is declining at an average rate of 0.42% per year due to sedimentation, corresponding to a mean sediment accumulation of $16.75 \text{ MCM yr}^{-1}$ per reservoir (Figure 6.5). By 2023, the average reservoir in this class has accumulated approximately 781 MCM of sediment, equivalent to nearly one-fifth (19.47%) of its original storage capacity (Figure 6.2). These values highlight the substantial cumulative burden of sedimentation on globally important water-storage systems.

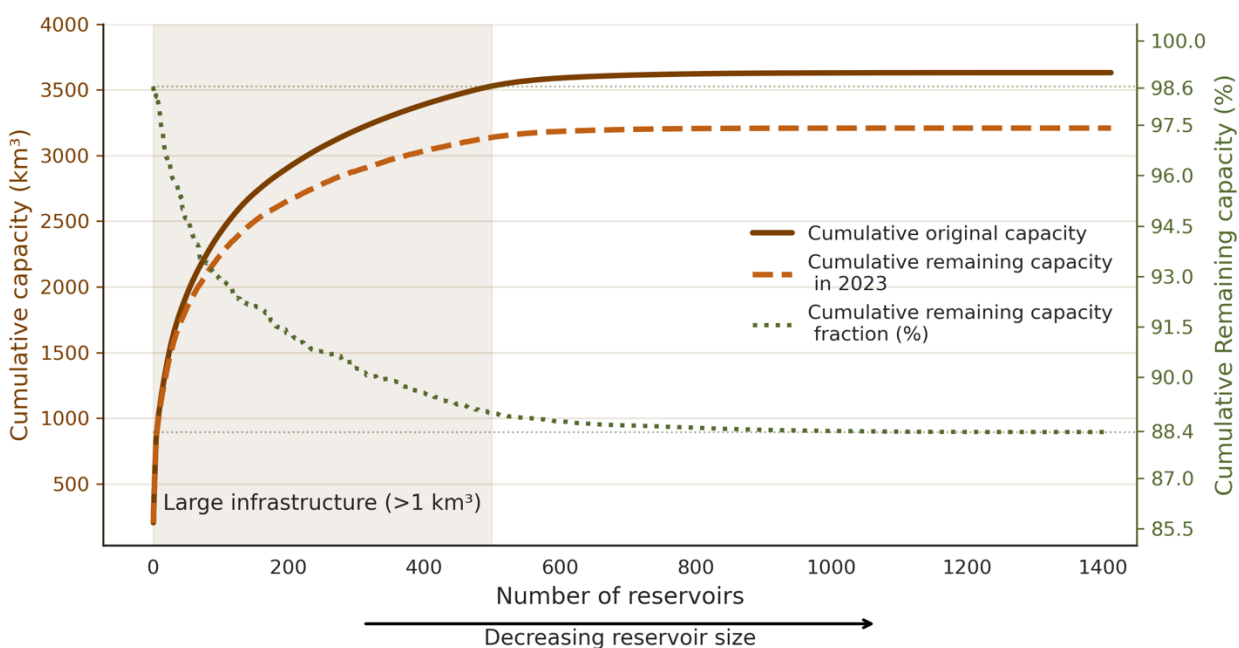


Figure 6.4 Cumulative global storage capacity in GLoRS ordered by decreasing design capacity. The solid line represents cumulative installed capacity; the dashed line shows cumulative remaining capacity in 2023 (absolute), and the dotted line indicates fraction of cumulative remaining capacity expressed as a percentage.

The SR map (Figure 6.5a) reveals strong regional clustering but no systematic relationship between reservoir size and sedimentation rate. Reservoirs of different capacities within the same basin often exhibit comparable SR values, indicating that sedimentation is governed primarily by catchment-scale controls—geomorphology, hydrology, land use, and climate—rather than storage capacity. High SR values occur in major sediment-rich systems including the Paraná, Nelson, Nile, Tigris–Euphrates, Indus, and Yellow River basins, whereas other regions display more moderate intensities.

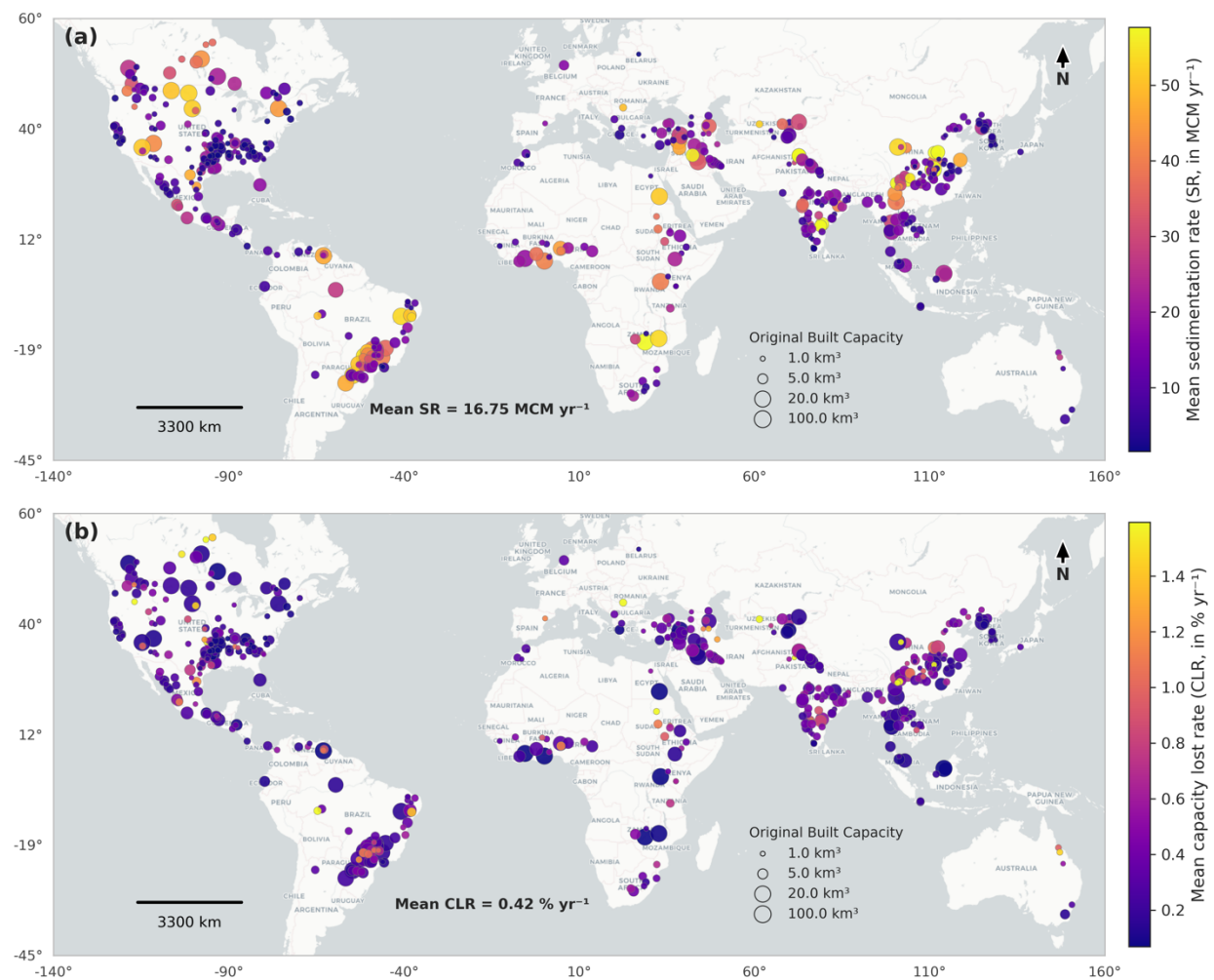


Figure 6.5 Spatial distribution of long-term (a) mean sedimentation rate (SR) and (b) mean annual capacity loss rate (CLR) for reservoirs with original design capacity $>1 \text{ km}^3$, representing major global water-storage infrastructure. Marker size denotes installed capacity of the reservoir.

In contrast, CLR (Figure 6.5b) exhibits a clear inverse relationship with reservoir size. Within the $>1 \text{ km}^3$ subset, smaller reservoirs experience higher proportional losses, while larger systems show comparatively lower annual percentage depletion. Because CLR normalizes sediment volume by design capacity, proportional loss is inherently scale dependent. Consequently, SR more directly reflects basin-scale sediment supply, whereas CLR captures infrastructure vulnerability relative to storage magnitude.

Together, these results demonstrate that volumetric sedimentation is controlled primarily by basin processes, while proportional storage depletion is modulated by infrastructure scale.

6.5.2.1. Country and Basin-Level Concentration of Estimated Storage Loss

To identify where sedimentation impacts are most concentrated, Figure 6.6a and Figure 6.6b rank countries and river basins by total sediment accumulation (TSA) within the large-reservoir subset, respectively. The top ten countries alone account for a substantial fraction of global storage loss, and the top ten basins similarly represent a large share of total depletion.

At the national scale, the United States accounts for 21.4% of total estimated global storage loss, exceeding 80 km^3 of cumulative capacity reduction, with approximately 17.7% of its installed reservoir capacity lost. Brazil, China, and India follow, contributing 12.9%, 12.1%, and 9.3% of global loss, respectively. While Brazil and China have each lost roughly 13% of their installed capacity, India exhibits higher proportional depletion at approximately 18.7%. Pakistan, although contributing a smaller share ($\sim 3\%$) to global loss, has experienced particularly severe proportional depletion, with nearly one-quarter of its installed reservoir capacity estimated to be lost.

At the basin scale, the Paraná and Mississippi basins contribute the largest shares, representing $\sim 10.7\%$ and $\sim 10.3\%$ of total global storage loss in this subset, with proportional losses of $\sim 13.5\%$ and $\sim 17.5\%$ of installed capacity, respectively. The Godavari basin contributes $\sim 5.8\%$ of global loss and exhibits particularly high proportional depletion, approaching one-quarter of installed large-scale storage.

These patterns demonstrate that fractional capacity loss becomes most informative when interpreted in the context of substantial volumetric sediment deposition, rather than in isolation.

This combined perspective reveals that basin- and country-level sedimentation risk is governed both by sediment supply and by the scale of installed storage.



Figure 6.6 Concentration and distribution of sedimentation within large-scale reservoirs ($>1 \text{ km}^3$). (a) Countries and (b) river basins ranked by total sediment accumulation (TSA). Left (orange) bars indicate absolute storage loss and percentage contribution to global loss within the large-reservoir subset; right bars show proportional capacity loss within each country or basin. (c) Median and inter-quantile range (IQR) distribution of long-term mean sedimentation rates (SR) across major basins and major climate zones.

6.5.2.2. Basin and Climate Controls on Sedimentation Rates

Long-term mean SR varies substantially across basins and climate zones (Figure 6.6c). Among basins containing at least five large reservoirs, the Yellow River exhibits the highest sedimentation intensity (median $\sim 47.7 \text{ MCM yr}^{-1}$; IQR $\sim 30\text{--}86 \text{ MCM yr}^{-1}$), followed by the Nelson (~ 32.5), Nile (~ 31.5), and Lower Aral Sea ($\sim 28.6 \text{ MCM yr}^{-1}$).

Most high-SR basins include reservoirs located in arid climates, underscoring the role of climatic controls on sediment production. Aggregation by climate zone reveals a systematic gradient: median SR and variability increase from cold to temperate to tropical to arid climates. This pattern is consistent with enhanced erosion and sediment mobilization under arid and tropical conditions, where limited vegetation cover and intense rainfall promote sediment yield.

Within the societally-critical large-reservoir subset, 193 reservoirs are located in temperate climates, 140 in tropical regions, 104 in arid regions, and 63 in cold climates, indicating that a substantial portion of globally important storage infrastructure is situated in sediment-prone environments.

6.5.2.3. Age Dependence of Sedimentation Rates

Sedimentation exhibits a modest age dependence within the large-reservoir subset (Figure 6.7). Long-term mean SR and CLR both show a gradual decline with increasing reservoir age, stabilizing after approximately 70–80 years. The presence of this trend in both volumetric (SR) and normalized (CLR) metrics indicates that the pattern is not solely a normalization artifact but reflects a modest reduction in sedimentation intensity over time.

Although the decline is small relative to overall variability, its consistency suggests weak but persistent age-related adjustment. Interquartile ranges remain wide across all ages, highlighting strong basin-to-basin heterogeneity. The underlying mechanisms—potentially involving changes in trapping efficiency, upstream sediment supply, or hydrological regulation—are beyond the scope of this study. Nevertheless, the gradual nature of the decline indicates that sedimentation remains an active process over reservoir lifetimes rather than diminishing rapidly after impoundment.

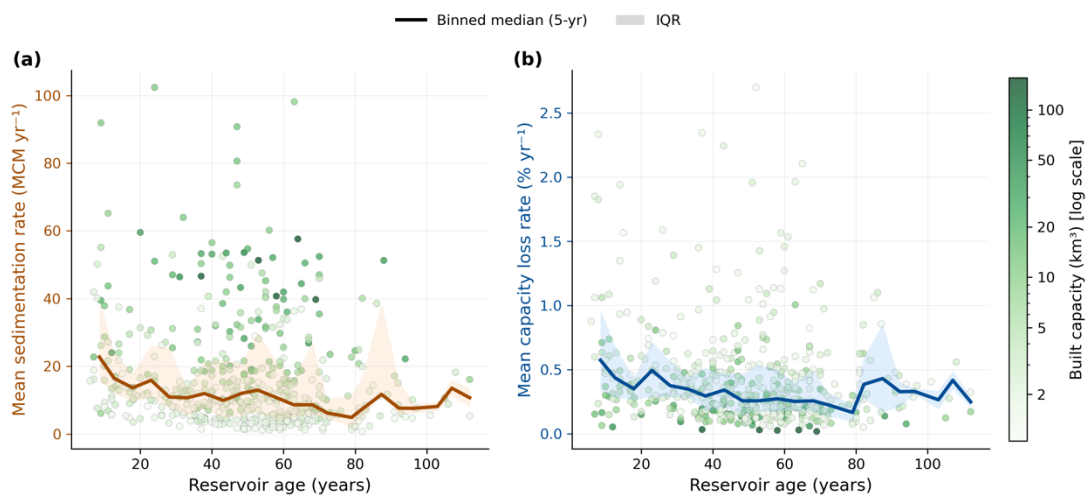


Figure 6.7 Relationship between reservoir age and long-term (a) mean sedimentation rate (SR) and (b) mean annual capacity loss rate (CLR) in large-scale reservoirs.

6.5.3. Temporal Patterns in Reservoir Sedimentation

To isolate temporal evolution from the progressive addition of newly constructed reservoirs, we restricted the global-mean analysis (Figure 6.8) to a fixed subset commissioned prior to 1984, ensuring complete time series over 1984–2023.

Figure 8a shows the annual mean sedimentation rate (SR), and Figure 8b the corresponding mean annual capacity loss rate (CLR), both with 5-year rolling means and variability envelopes. Mean SR oscillates around a long-term average of 6.09 MCM yr⁻¹, exhibiting multi-year variability but no pronounced monotonic trend over four decades. Variability widens modestly in later years, indicating increasing heterogeneity among reservoirs rather than a systematic global intensification.

In contrast, CLR—normalized by original design capacity—appears smoother and exhibits a gradual decline from the late 1980s to recent years, with a long-term mean of $1.32\% \text{ yr}^{-1}$. The attenuation of oscillations likely reflects aggregation and normalization effects that dampen basin-scale variability. However, the persistence of a declining tendency despite this smoothing suggests a modest structural adjustment in normalized storage depletion rates over time.

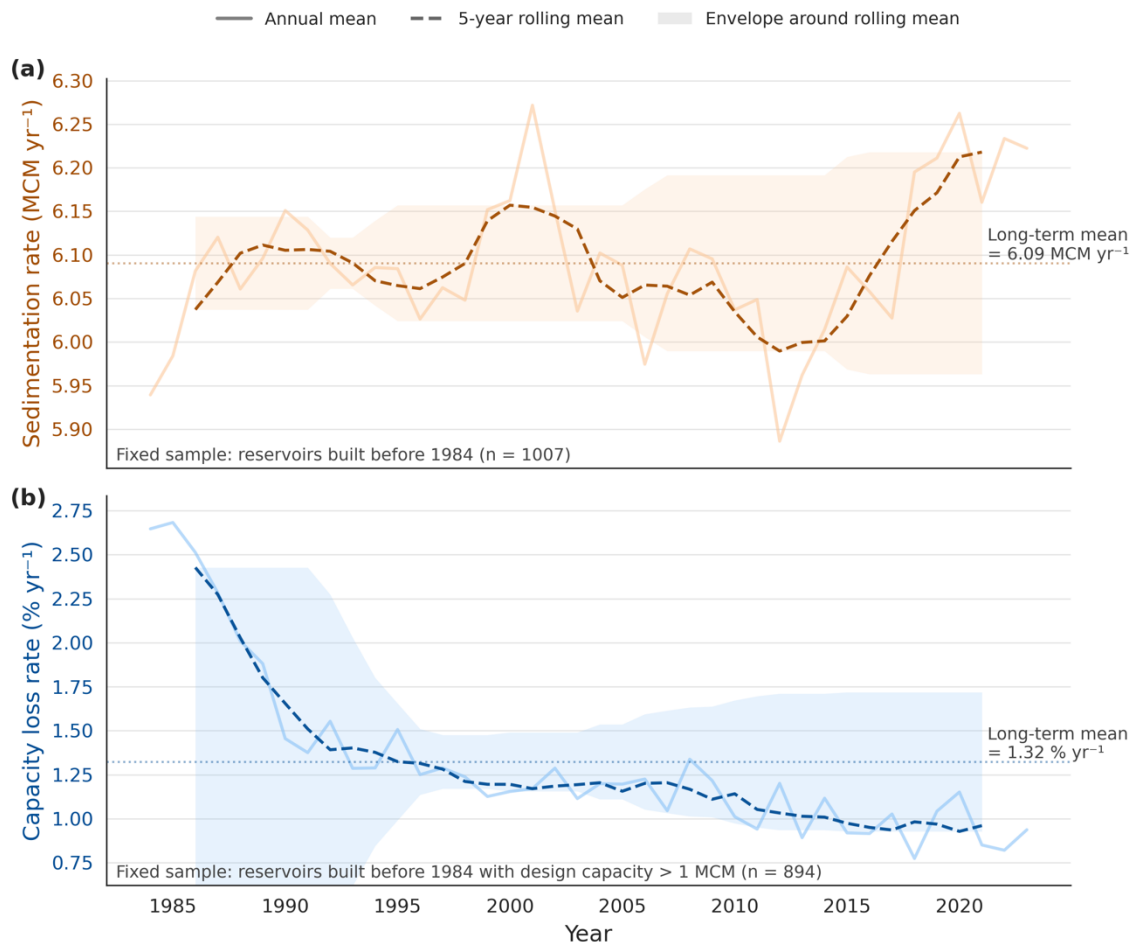


Figure 6.8 Temporal evolution of global annual mean (a) sedimentation rate (SR) and (b) capacity loss rate (CLR) from 1984–2023, calculated using a fixed sample of reservoirs constructed prior to 1984 to ensure consistent time-series coverage. For (b) the reservoir subset was further limited to those which were larger than 1MCM in size. The solid line represents the annual mean, the dotted line indicates the 5-year rolling mean, and the shaded envelope denotes variability around the smoothed trend.

Together, these patterns highlight the distinction between volumetric sediment supply (SR), which captures basin-scale variability, and proportional depletion (CLR), which integrates sedimentation with infrastructure scale. Despite modest moderation in CLR, sedimentation remains a sustained, long-term influence on global storage capacity.

6.5.3.1. Regional Variability Across Continents and Climate Zones

Regional contrasts in sedimentation variability were evaluated using spatial and temporal dispersion metrics (Figure 6.9). Spatial variability was defined as the interquartile range (IQR) of long-term mean SR across reservoirs within each region, while temporal variability was defined as the IQR of annual regional mean SR over 1984–2023. Median SR is indicated by color.

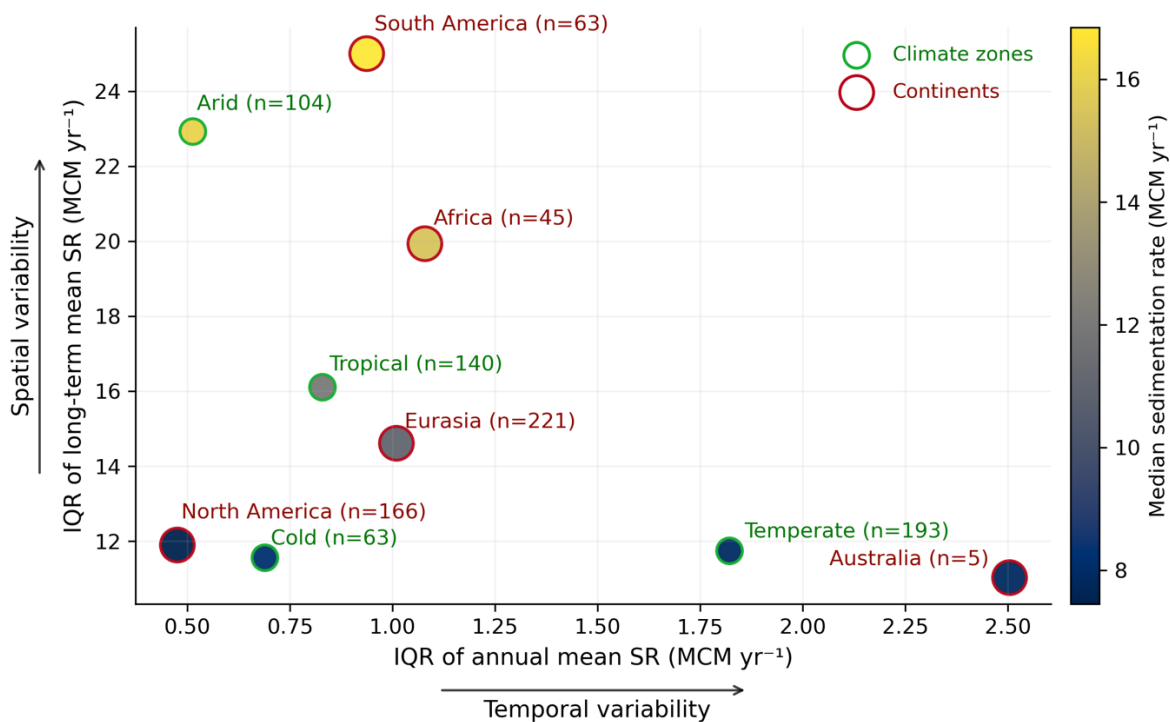


Figure 6.9 Regional contrasts in sedimentation variability based on spatial and temporal dispersion metrics. Spatial variability is defined as the interquartile range (IQR) of long-term mean sedimentation rate (SR) across reservoirs within each region, while temporal variability represents the IQR of annual regional mean SR over 1984–2023. Marker color indicates median SR. Larger markers denote continents, and smaller markers represent climate zones.

Strong contrasts emerge across continents. South America exhibits the highest spatial variability ($\text{IQR} \approx 25.0 \text{ MCM yr}^{-1}$) and the highest median SR ($\sim 16.8 \text{ MCM yr}^{-1}$), yet comparatively low temporal variability ($\sim 0.94 \text{ MCM yr}^{-1}$), indicating heterogeneous basin-scale sediment supply but relatively stable regional means. Africa shows similarly high spatial variability ($\sim 19.9 \text{ MCM yr}^{-1}$) and elevated median SR ($\sim 15.5 \text{ MCM yr}^{-1}$).

Australia displays the highest temporal variability ($\sim 2.50 \text{ MCM yr}^{-1}$) despite lower median SR ($\sim 7.85 \text{ MCM yr}^{-1}$); however, this likely reflects the small sample size ($n = 5$) rather than continent-wide hydroclimatic instability.

Climate-zone aggregation reveals a comparable structure. Arid regions exhibit high spatial variability ($\text{IQR} \approx 22.9 \text{ MCM yr}^{-1}$) and elevated median SR ($\sim 16.1 \text{ MCM yr}^{-1}$), yet the lowest temporal dispersion ($\sim 0.51 \text{ MCM yr}^{-1}$), consistent with strong geomorphic controls operating within broadly sediment-rich landscapes. Temperate regions display the greatest temporal variability ($\sim 1.82 \text{ MCM yr}^{-1}$) despite lower median SR ($\sim 7.93 \text{ MCM yr}^{-1}$), indicating heightened sensitivity to interannual hydroclimatic fluctuations. Cold regions exhibit lower median SR ($\sim 8.17 \text{ MCM yr}^{-1}$) and relatively low spatial dispersion ($\sim 11.56 \text{ MCM yr}^{-1}$).

Overall, spatial heterogeneity in sediment supply and temporal variability in sedimentation intensity are largely decoupled. Basin-scale contrasts and interannual variability operate independently, underscoring the multi-scale structure of global reservoir sedimentation dynamics.

6.5.3.2. ENSO–Sedimentation Relationship

To evaluate ENSO sensitivity, we computed Pearson correlations between annual sedimentation rate (SR) anomalies and Niño 3.4 sea surface temperature (SST) anomalies for each reservoir (Figure 6.10). Positive correlations indicate enhanced sedimentation during El Niño phases; negative correlations indicate enhancement during La Niña.

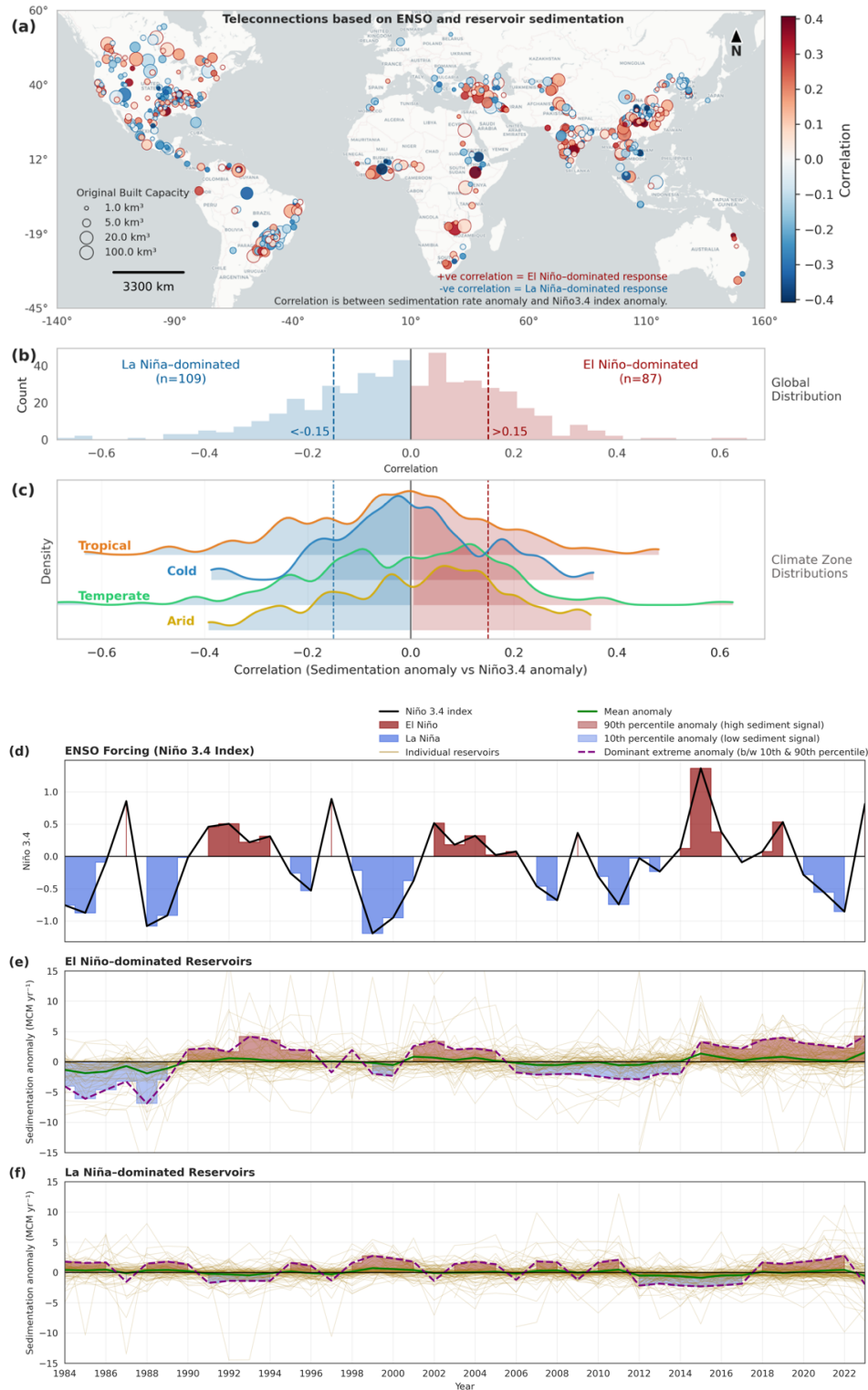


Figure 6.10 ENSO–sedimentation relationships across large-scale reservoirs. (a) Spatial distribution of Pearson correlation coefficients between annual sedimentation rate (SR) anomalies and Niño 3.4 SST anomalies. (b) Global distribution of correlation values, with

thresholds used to classify El Niño– and La Niña–dominated reservoirs. (c) Correlation distributions by Köppen–Geiger climate zone, illustrating the geographically structured nature of ENSO teleconnections in reservoir sedimentation. (d) Annual Niño 3.4 SST anomalies, with El Niño phases shown in red and La Niña phases in blue. (e) Sedimentation rate (SR) anomalies for reservoirs classified as El Niño–dominated, showing individual reservoir time series (light lines), the mean anomaly (solid line), and the dominant extreme anomaly (dashed line). (f) Same as (e), but for La Niña–dominated reservoirs. Dominant extreme anomalies represent the larger-magnitude signal between the 10th and 90th percentile SR anomalies for each year, highlighting the amplification of extreme sedimentation events under ENSO forcing.

ENSO Teleconnections

The spatial distribution of correlations (Figure 6.10a) exhibits clear geographic clustering, with reservoirs of similar ENSO response forming coherent regional groupings. This pattern is consistent with large-scale hydroclimatic teleconnections rather than isolated local effects. Positive correlations (El Niño–associated enhancement) occur in parts of South Asia, southern China, the Middle East, southern Africa, and Australia, whereas negative correlations (La Niña–associated enhancement) dominate in eastern Africa, portions of Brazil, central Europe, and parts of the United States. These patterns broadly align with known ENSO-driven precipitation anomalies.

Using a threshold of $|r| > 0.15$, 87 reservoirs were classified as El Niño–dominated and 109 as La Niña–dominated (Figure 6.10b). The near symmetry between positive and negative responses explains the weak correlation between global-mean SR anomalies (Figure 6.8a) and ENSO forcing ($r \approx 0.06$), as opposing regional signals largely cancel at the global scale. ENSO-driven sedimentation variability is therefore geographically structured rather than globally coherent.

Climate-Zone Perspective

Correlation distributions aggregated by climate zone (Figure 6.10c) remain approximately symmetric around zero, indicating that ENSO impacts are not determined solely by climatic classification. Tropical and temperate reservoirs exhibit broader correlation ranges than cold regions, suggesting greater ENSO sensitivity. However, both El Niño– and La Niña–dominated

reservoirs coexist within individual climate zones, reinforcing the geographically structured nature of teleconnections.

ENSO Forcing and Extreme Sedimentation

To further examine how ENSO variability manifests in sedimentation dynamics, Figure 6.10(d–f) presents composite anomaly behavior for reservoirs classified as El Niño–dominated and La Niña–dominated.

The upper panel (Figure 6.10d) shows the annual Niño 3.4 SST anomaly time series. The middle and lower panels display sedimentation anomalies for reservoirs classified as El Niño–dominated and La Niña–dominated, respectively. Individual reservoir time series are shown in light background traces, while the regional mean anomaly is indicated by the solid green curve.

To isolate extreme sedimentation responses, we evaluated the 10th and 90th percentile sedimentation anomalies each year. The larger-magnitude percentile anomaly was designated as the *dominant extreme anomaly* (purple dashed curve), with positive (90th percentile) anomalies shown in red and negative (10th percentile) anomalies shown in blue. In El Niño–dominated reservoirs, positive extreme sedimentation anomalies align closely with positive Niño 3.4 SST anomalies. In La Niña–dominated reservoirs, dominant anomalies are phase-inverted, with enhanced sedimentation during La Niña conditions. These two curves, the cross-reservoir mean anomaly and the dominant extreme anomaly in a given year, are referred to below as the mean composite and the dominant-extreme composite, respectively.

Importantly, the mean sedimentation anomaly across reservoirs remains near zero in both panels, showing only weak directional alignment with ENSO forcing. This contrast indicates that ENSO primarily modulates the tails of the sedimentation distribution rather than systematically shifting the central tendency of sediment deposition. In other words, ENSO influences sedimentation intensity predominantly through extreme events rather than through sustained changes in mean deposition rates. This amplification, the dominant-extreme composite's regression slope against Niño 3.4 exceeding the mean composite's slope by a significantly larger margin, was statistically significant (moving-block bootstrap, 95% CI on the slope-magnitude difference excludes zero in both groups), and this pattern was absent when the same test was applied to randomly composed reservoir groups of matching size (empirical $p < 0.001$ for both groups), indicating that the

amplification is specific to the ENSO-classified populations rather than a generic consequence of aggregating anomalies across reservoirs (Appendix Section 12.4).

This robustness to the classification method itself extends further: the conclusion does not depend on the specific $|r| \geq 0.15$ cutoff used to build the classified groups; justification for this cutoff is provided in Appendix Section 12.4. Repeating the composite-amplification and null-permutation tests at alternative thresholds from $|r| \geq 0.10$ to $|r| \geq 0.30$ (Table 12.4) leaves the result unchanged throughout: the bootstrap confidence interval on the slope-magnitude difference excludes zero and the null-permutation p-value stays ≤ 0.0025 at every cutoff tested, with the amplification ratio remaining within a similar $2.8\times\text{--}4.7\times$ band rather than appearing or disappearing near 0.15 (Figure 12.2).

Together, the spatial clustering of correlations and the dominance of extreme anomalies indicate that ENSO influences reservoir sedimentation primarily through geographically organized, event-driven processes rather than sustained changes in mean sediment supply.

6.5.3.3. Long-term trends in Sedimentation Rate

Long-term trends in sedimentation rate (SR) were evaluated for the large-reservoir subset using the Mann–Kendall test, with only statistically significant trends ($p < 0.05$) interpreted (Figure 6.11).

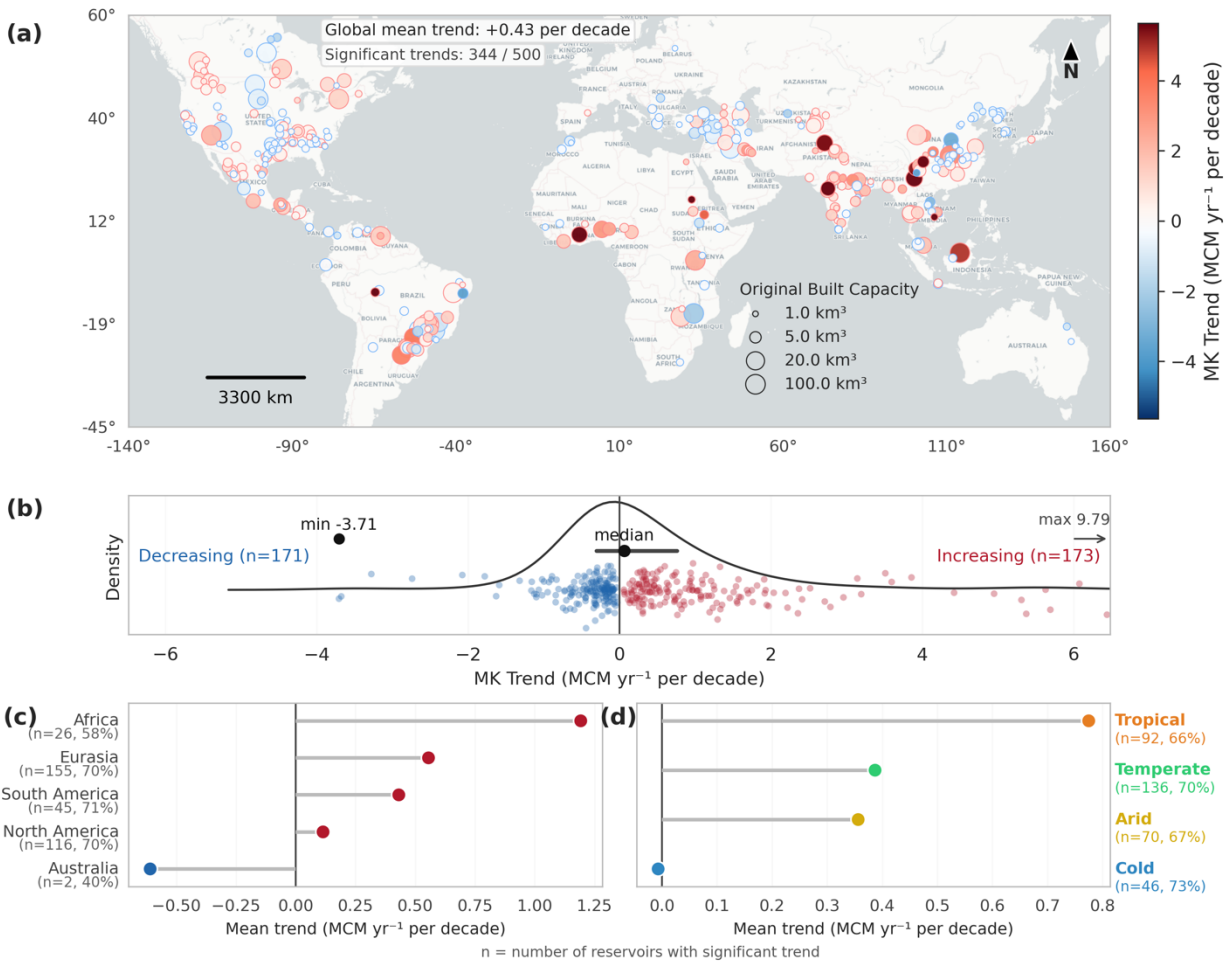


Figure 6.11 Long-term trends in sedimentation rates across large-scale reservoirs. (a) Spatial distribution of statistically significant Mann–Kendall trends ($p < 0.05$) in sedimentation rate (SR), with colors indicating increasing and decreasing trends. (b) Distribution of significant trend magnitudes (MCM yr^{-1} per decade). (c) Mean SR trend across continents and (d) across climate zones; panels (c) and (d) also indicate the number of reservoirs exhibiting statistically significant trends within each region.

Significant trends exhibit clear geographic clustering (Figure 6.11a), indicating basin- and regional-scale structuring rather than random variation. Upward trends dominate parts of South Asia, southern Brazil, and West Africa, whereas Europe, portions of the central United States, and northeastern China show predominantly declining SR.

Of the 500 large reservoirs analyzed, 344 exhibit significant trends: 173 increasing and 171 decreasing (Figure 6.11b). Trend magnitudes range from -3.71 to $+9.79$ MCM yr^{-1} per decade, though most lie between -1 and $+2$ MCM yr^{-1} per decade. These values represent the decadal rate of change in annual SR, with positive trends indicating intensification and negative trends indicating decline. Despite the near balance in counts, the global mean trend is positive ($+0.43$ MCM yr^{-1} per decade), indicating slightly larger magnitudes among upward trends.

Regional aggregation reveals additional contrasts (Figure 6.11c–d). Africa exhibits the strongest mean upward trend (>1 MCM yr^{-1} per decade), with $\sim 58\%$ of reservoirs significant. Eurasia, South America, and North America show broadly positive mean trends, with $\sim 70\%$ of reservoirs significant. Australia displays a net downward mean trend, though based on only two significant reservoirs.

Climate-zone analysis shows the largest mean upward trends in tropical regions, followed by temperate and arid zones, while cold regions exhibit a net decline. Across climate zones, $66\text{--}73\%$ of large reservoirs display significant trends, highlighting the widespread nature of long-term sedimentation change.

Overall, although the global mean trend is modest, sedimentation rates are undergoing pronounced regional restructuring, consistent with hydroclimatic and land-surface controls rather than uniform global forcing.

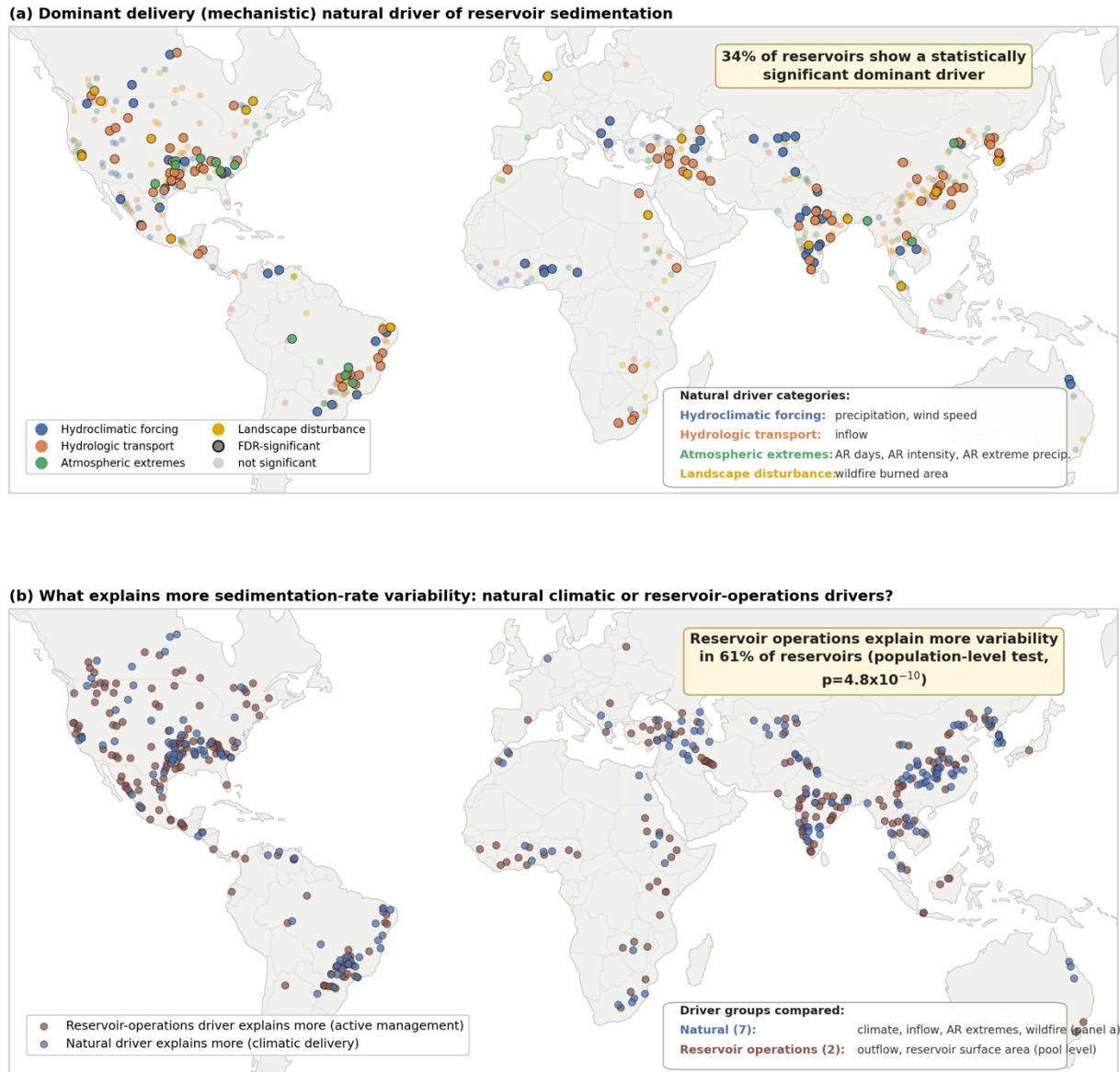
6.5.3.4. Mechanistic Drivers of Climate–Sedimentation Linkages

To identify which physical pathways underlie sedimentation-rate variability, we tested the direct reservoir-level relationship between each reservoir's sedimentation-rate anomaly and seven candidate natural (“delivery”) drivers. These drivers span hydroclimatic, hydrologic, atmospheric, and landscape-disturbance mechanisms. We used autocorrelation-corrected, per-category Šidák-adjusted correlations at zero- and one-year lag (Appendix Section 12.5). Inflow (hydrologic transport) was the single most common dominant driver (39.3% of reservoirs), followed by wildfire burned-area fraction (18.4%) and wind speed (15.2%) (Figure 6.12a); 34.5% of reservoirs had a statistically significant dominant driver after FDR correction. A lag-1 (delayed) relationship was strongest for over a third of reservoirs, underscoring the value of testing delayed as well as

contemporaneous mobilization. The rate of having a significant dominant driver did not differ systematically by ENSO-response group (Table 12.4).

A clearer result emerged from directly comparing each reservoir's best natural (delivery) driver against its best reservoir-operations (retention) driver (Table 12.5; Figure 6.12b). Because delivery draws from more candidate variables (7) than retention (2), a raw comparison structurally favors delivery; even so, retention's raw effect size was larger in 58.7% of reservoirs ($p = 1.3 \times 10^{-5}$) — already significant despite the handicap. Correcting for the candidate-count imbalance with the same Šidák adjustment, retention was the more significant explanatory factor in 61.3% of reservoirs ($p = 4.8 \times 10^{-10}$) — an even stronger result. Active reservoir management (outflow regulation, pool-level operation) explains sedimentation-rate variability more often than natural climatic delivery mechanisms at these reservoirs, adding quantitative support to Appendix Section 12.3's discussion of active sediment management.

This reservoir-operations dominance varies geographically (Figure 6.12b). It is strongest in Mexico (84% of reservoirs), Iran (80%), Turkey (71%), the United States (67%), Canada (65%), and India (65%), all exceeding the 61.3% population-level rate. China is the principal exception: natural climatic delivery drivers explain sedimentation-rate variability more often than reservoir operations in 54% of Chinese reservoirs, the reverse of the global pattern, consistent with a large population of comparatively young reservoirs on rivers with substantial, still-evolving upstream sediment supply (e.g., Loess Plateau catchments). The identity of the dominant natural driver (Figure 6.12a) also varies regionally: wind speed is disproportionately common in Iran (30%) and Turkey (24%) relative to the 15.2% global rate, consistent with more arid, wind- and dust-influenced catchments, whereas inflow remains the single most common dominant driver in every major reservoir-owning country, including China (46%) and India (43%). Sample sizes are too small in Australia ($n=5$) and Europe ($n=7$) to support continental-level conclusions there.



Note: Mechanism categories differ in candidate-variable count (hydrologic transport: 1 vs. atmospheric extremes: 3; natural: 7 vs. reservoir-operations: 2 in panel b) - a per-category Sidak correction accounts for this throughout, so categories with more candidates are not favored merely by more chances to show a large correlation; AR stands for Atmospheric River.

Figure 6.12 Dominant natural driver category (a) and reservoir-operations-versus-delivery dominance (b) for large-scale infrastructure reservoirs. (a) Most common statistically dominant natural (delivery) driver category per reservoir. (b) Reservoirs where the best reservoir-operations (retention) driver explains more sedimentation-rate variability than the best natural (delivery) driver, versus the reverse.

6.5.4. Process-Based Case Study Analysis

6.5.4.1. Cascading Reservoir Infrastructure: Three Gorges-Gezhouba System

The Three Gorges–Gezhouba cascade provides a clear example of infrastructure-driven sediment reorganization. Three Gorges Dam (TGD), completed in 2006 and reaching full impoundment in 2010, is located ~38 km upstream of the older Gezhouba Dam, forming a tightly coupled cascade system (Figure 6.13b).

Figure 6.13a shows annual sedimentation rates (SR) for both reservoirs, Figure 6.13b their configuration, and Figure 6.13c pre- (≤ 2010) and post- (> 2010) distributions. Prior to 2010, SR remained relatively stable at both reservoirs (TGD: ~ 58.7 MCM yr^{-1} ; Gezhouba: ~ 38.9 MCM yr^{-1}). After full impoundment, a clear divergence emerges. TGD continues to accumulate sediment at high rates (~ 60.1 MCM yr^{-1}), while Gezhouba experiences a marked decline (~ 33.6 MCM yr^{-1}), most pronounced during 2011–2013 before stabilizing at a lower level.

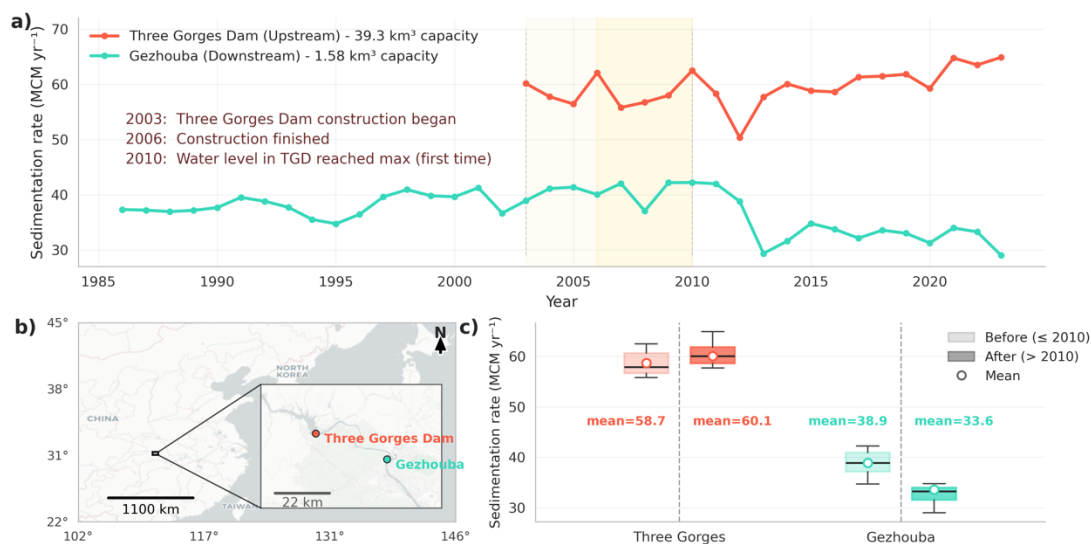


Figure 6.13 Cascading infrastructure effects in the Three Gorges–Gezhouba system. (a) Annual sedimentation rate (SR) time series for Three Gorges Dam (TGD) and Gezhouba Dam, illustrating divergence following full impoundment of TGD (~ 2010). (b) Geographic configuration of the cascade along the Yangtze River. (c) Comparison of SR distributions before (≤ 2010) and after (> 2010) full impoundment, demonstrating sustained high sedimentation at TGD and reduced deposition at Gezhouba consistent with upstream sediment trapping.

This pattern is consistent with cascade trapping theory. As a large upstream impoundment ($\sim 39 \text{ km}^3$), TGD intercepts a substantial fraction of upstream sediment, reducing downstream delivery. The sustained high SR at TGD combined with the downstream decline at Gezhouba represents a coherent trapping signal rather than stochastic variability. Similar downstream reductions following TGD impoundment have been documented independently (Huang et al., 2013; Yu et al., 2013).

6.5.4.2. The Wenchuan Earthquake: Zipingpu Reservoir

The 2008 Wenchuan earthquake ($M_w 7.9$) triggered widespread landsliding in the upper Min Jiang basin, dramatically increasing sediment availability. Unlike engineered perturbations, tectonic disturbances introduce large sediment pulses whose downstream expression depends on subsequent hydroclimatic conditions.

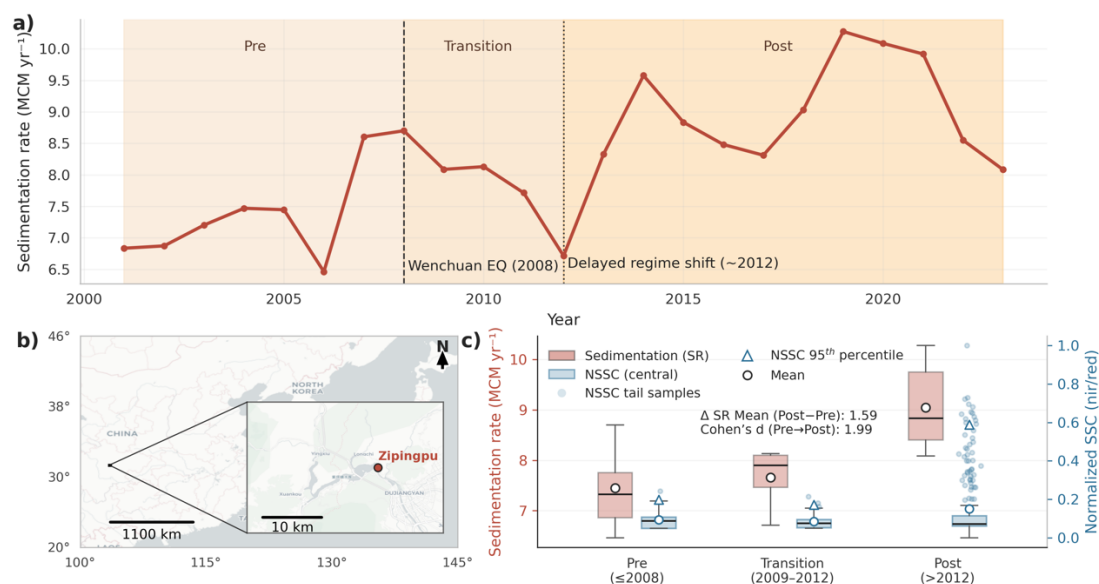


Figure 6.14 Tectonic disturbance and delayed sediment regime shift following the 2008 Wenchuan earthquake. (a) Annual sedimentation rate (SR) time series for Zipingpu reservoir, showing a delayed but persistent post-seismic increase in sedimentation. (b) Geographic location of the reservoir. (c) Comparison of sedimentation and remotely sensed normalized suspended sediment concentration (NSSC) distributions across pre-seismic (≤ 2008), transition (2009–2012),

and post-shift (>2012) periods, highlighting elevated extreme turbidity events and a regime shift in sediment dynamics.

Figure 6.14a presents SR at Zipingpu reservoir, located downstream of the affected region. Figure 6.14b shows its location, and Figure 6.14c compares sedimentation and normalized suspended sediment concentration (NSSC) across pre-seismic (≤ 2008), transition (2009–2012), and post-shift (>2012) periods.

Before 2008, SR averaged $\sim 7 \text{ MCM yr}^{-1}$. Although a modest increase occurs immediately after the earthquake, a sustained regime shift emerges around 2012, with post-shift SR increasing by $\sim 1.59 \text{ MCM yr}^{-1}$ relative to pre-seismic conditions. The effect size is large (Cohen's $d \approx 1.99$), indicating a structural transition rather than short-term variability.

This delayed amplification is consistent with post-seismic sediment cascades. Landslide-derived material was not evacuated immediately; instead, its downstream mobilization depended on subsequent monsoon-driven transport. Years with limited runoff muted the initial signal, whereas later high-flow seasons remobilized stored debris, producing elevated sediment flux (Zhang et al., 2019).

Remotely sensed NSSC analysis clarifies the mechanism (Figure 6.14c). The central tendency shifts modestly, but the upper tail increases substantially after 2012, with more frequent and higher-magnitude turbidity extremes. ENSO results (Section 6.5.3.2) indicate that such extreme events dominate sedimentation responses to climatic forcing. Here, increased sediment availability combined with hydroclimatic variability produces amplified extreme deposition rather than a uniform rise in mean SR.

The persistence of elevated extremes nearly a decade after the earthquake underscores the long memory of tectonically perturbed sediment systems (Francis et al., 2022; Koi et al., 2008). Unlike the immediate cascade trapping response in Section 6.5.4.1, the Wenchuan case illustrates delayed, climate-modulated regime restructuring following geomorphic disturbance.

The ability of GLoRS to resolve both engineered cascade effects and long-memory geomorphic responses at the individual-reservoir scale supports the physical interpretability of the broader global patterns identified above.

6.6. Discussion

6.6.1. A Satellite-Era Framework for Global Sedimentation Monitoring

This study provides the first globally consistent, multi-decadal assessment of reservoir sedimentation derived from satellite-based Earth observations. The GLoRS dataset on reservoir sedimentation is a culmination of a coordinated monitoring framework integrating remote sensing, in-situ sediment records, terrain analysis, land-cover dynamics, reanalysis climate products, and machine-learning-based sediment estimation. By linking actual reservoir operations from RAT (rather than relying on operational assumptions), quality-controlled global reservoir sediment training data from GRILSS, and the globally applicable sedimentation estimation tool as in RECLAIM, this work reconstructs time-varying sedimentation dynamics over multiple decades at global scale.

The GLoRS dataset enables for the first time a unified evaluation of volumetric sediment deposition, proportional storage loss, climate teleconnections, and long-term trends—providing an observationally constrained view of how much reservoir storage capacity is likely available now.

6.6.2. Sedimentation as Structural Constraint on Global Surface Water Storage

Reservoir sedimentation is often treated as a long-term maintenance issue, but it is rarely discussed as a structural constraint on global surface water infrastructure. Our analysis shows that sediment-driven storage decline is neither negligible nor spatially random. Instead, it reflects the coupled influence of basin geomorphology, hydroclimate, and infrastructure scale.

The estimated rate of storage loss indicates that sedimentation is steadily eroding functional capacity across major reservoirs worldwide. Although annual percentage losses appear modest, their cumulative effect over decades is substantial. Approximately 11.6% of the installed storage capacity considered in this study has been lost by 2023. This estimate is comparable to Perera et al. (2023), who reported a 16% global storage loss by 2022 (based on a larger installed base of ~6,300 km³).

Similarly, Wisser et al. (2013) reported a median capacity loss rate of 0.35% yr⁻¹ for reservoirs larger than 1 MCM, which aligns closely with our estimates. This gradual but persistent decline challenges a common assumption in global and regional water assessments (Hou et al., 2022; Li

et al., 2023; Hossain et al., 2023): that installed storage capacity remains effectively static over planning horizons. In reality, storage capacity is dynamic and progressively diminishing, with implications for irrigation reliability, hydropower generation, and flood buffering (Wisser et al., 2013; Perera et al., 2023).

The strong scale dependence identified here further complicates risk assessment. Large reservoirs accumulate most of the global sediment volume, yet smaller systems experience faster proportional depletion. Vulnerability therefore cannot be inferred from size alone. Basin sediment supply and infrastructure scale interact to determine both the pace and form of storage decline. Water security assessments that rely solely on installed capacity may therefore overestimate effective storage availability.

6.6.3. Spatial Structuring and Climate Teleconnections Intensifying Sediment Extremes

A central finding of this study is that sedimentation dynamics are hydroclimatically organized rather than globally synchronized. Both monotonic trends and ENSO teleconnections cluster geographically, reflecting regional climate controls on sediment mobilization.

Importantly, ENSO influences sedimentation primarily by amplifying extremes rather than by systematically shifting mean deposition. This behavior is consistent with the episodic nature of sediment transport, which is disproportionately governed by high-magnitude precipitation events (Thothong et al., 2011; García-Ruiz et al., 2002). Under such conditions, changes in climate variability may matter more than gradual shifts in average runoff.

The observed global increase in sedimentation rates, though moderate, suggests that sediment supply is not stationary. Intensification of extreme precipitation in several regions (Donat et al., 2016; Sun et al., 2021) may be contributing to elevated sediment pulses. If hydroclimatic variability continues to amplify high-magnitude transport events, reservoirs may experience more episodic and less predictable sediment loading. Such dynamics challenge sediment management strategies that assume relatively steady accumulation rates.

In this context, sedimentation emerges not only as a geomorphic process, but as a climate-mediated infrastructure risk.

6.6.4. Implications for Water Infrastructure Resilience in a Changing Climate

The contrasting case studies from China illustrate two distinct but complementary drivers of sediment regime reorganization: engineered hydraulic alteration and geomorphic disturbance.

In the Three Gorges–Gezhouba cascade, upstream trapping rapidly restructured downstream sediment flux, demonstrating how infrastructure can reorganize sediment connectivity at basin scale (Yang et al., 2019; Piasecka et al., 2025). In contrast, the Wenchuan earthquake triggered a delayed, climate-modulated regime shift driven by elevated turbidity extremes over subsequent years. This case illustrates how geomorphic disturbances can influence sediment dynamics for a decade or more (East & Sankey, 2020).

Together, these examples underscore that sediment risks arise from both engineered interventions and external geomorphic shocks, operating on different timescales. Immediate hydraulic reconfiguration and delayed climate-regulated sediment cascades pose fundamentally different management challenges.

Under intensifying hydroclimatic variability, reservoirs may increasingly experience sedimentation dominated by high-magnitude, low-frequency transport events. This shift—from gradual background accumulation toward extreme-driven pulses—has direct implications for storage reliability, spillway safety, and sediment management planning (Molina et al., 2024; Cifres, 2025). Infrastructure resilience strategies must therefore consider not only long-term cumulative loss, but also the growing influence of episodic sediment surges.

More broadly, these findings suggest that reservoir sedimentation should be explicitly incorporated into climate adaptation frameworks. Effective storage is declining, variability is increasing, and sediment delivery is becoming more episodic. Planning based solely on installed capacity or historical averages may underestimate future constraints on water supply and flood control.

6.7. Conclusion

For decades, reservoir sedimentation has been recognized as a persistent challenge. Yet its rate, scale, geographic concentration, and relationship to climate variability, tele-connected or land deformation processes have not been resolved consistently at the global scale. This study addresses that gap by providing the first globally consistent, multi-decadal assessment of sediment-driven storage loss derived from Earth observations across 1,412 reservoirs worldwide.

An estimated 88.4% of global storage capacity remains as of 2023 in these large dams. Storage is declining at an average rate of 0.42% per year due to sedimentation, with the average large reservoir having already lost nearly one-fifth of its original capacity. Climate variability influences sedimentation primarily through amplified extremes rather than steady shifts in mean deposition.

Reservoir-level attribution links sedimentation-rate variability to specific natural pathways — most commonly inflow, followed by wildfire-related disturbance and wind-driven hydroclimatic forcing — though how a reservoir is operated (human decisions about outflow release and pool level) explains this variability more often than any natural climatic driver, in 61.3% of the roughly 500 large-scale infrastructure reservoirs studied. Sediment management therefore deserves treatment as a primary, not secondary, control on reservoir capacity trajectories in future global projections.

Together, these findings converge on a fundamental question for global water security: How fast is the world losing reservoir storage in a changing climate? For the first time, that question can be answered consistently at planetary scale. Our study and the GLoRS v1.0 dataset transform sedimentation from a hidden, poorly quantified process into a predictable global signal. We provide a consistent, satellite-derived benchmark against which future change can be tracked—year by year, basin by basin. More broadly, our findings suggest that reservoir sedimentation trends and drivers should be explicitly incorporated into climate adaptation frameworks to futureproof our current fleet of reservoirs. With four decades of resolved reservoir storage loss, we can now identify where resilience is eroding, where climate-amplified extremes are accelerating risk, and where intervention is most urgent. In doing so, this study reframes reservoir sedimentation not as a slow inevitability, but as a predictable and manageable component of global water security in a warming world.

Chapter 7. Conclusion and Future Recommendations

7.1. Synthesis

This dissertation set out to answer a deceptively simple question: how much reservoir storage remains on Earth, and how rapidly is it being lost? Answering that question at planetary scale requires solving four tightly coupled problems—monitoring, data curation, estimation, and assessment—none of which could be solved in isolation. Chapters 2 through 6 addressed each of these in turn, building on one another to produce, for the first time, a globally consistent, multi-decadal, satellite-based accounting of reservoir sedimentation. Chapter 2 and Chapter 3 delivered the operational monitoring backbone (RAT 3.0 and its Python library). Chapter 4 closed the training-data gap with GRILSS, the first open global dataset of observed reservoir sedimentation. Chapter 5 used that dataset to build RECLAIM, a globally scalable machine-learning framework for estimating sedimentation from satellite-observable inputs. Chapter 6 integrated these three components to produce the Global Long-term Reservoir Sedimentation (GLoRS) dataset and quantify the state and trajectory of global reservoir storage in a changing climate. This concluding chapter distills the main findings of each chapter, reflects on their collective contribution, and outlines the research directions that should be pursued next.

7.2. Chapter 2: A Scalable Platform for Reservoir Monitoring (RAT 3.0)

Chapter 2 described the complete redesign of the Reservoir Assessment Tool into version 3.0, a modular, open-source software platform that couples satellite Earth observation with hydrological modeling to monitor reservoir dynamics—inflow, outflow, storage change, evaporation, and surface area—at a 2-to-5-day cadence. The redesign targeted four long-standing barriers to community adoption: scalability, computational efficiency, ease of use, and global applicability. The resulting fourteen-step modular architecture runs on a standard laptop as well as on high-performance clusters, supports parallelized downloading and processing of meteorological data, and can be configured for any reservoir system worldwide. Setup time, which had required three to four months in RAT 2.0, was reduced to approximately one week.

Beyond the software itself, Chapter 2 demonstrated the operational maturity of RAT 3.0 through independent deployments across the Mekong, Columbia, Nile, Indus, Tennessee, and Cumberland

basins, as well as its adoption by the Asian Disaster Preparedness Center as the operational system for the Mekong River Commission. These deployments established that satellite-based reservoir monitoring can be delivered not only as a research prototype but as production infrastructure. The chapter's core contribution is therefore both technical and institutional: RAT 3.0 provides the monitoring substrate on which the rest of this dissertation is built, and its open-source, community-oriented design lowers the barrier for a self-sustaining global user community to continue improving it.

7.3. Chapter 3: Packaging RAT for the Global Community

Chapter 3 addressed a different but equally critical barrier: distribution. A capable tool is of little practical value if its installation is fragile, its contributions unverifiable, and its updates untracked. By packaging RAT 3.0 as a Conda library hosted on conda-forge, establishing a continuous-integration and continuous-development pipeline through GitHub Actions, and providing verified test basins, command-line utilities, a configuration toolbox, and comprehensive documentation, Chapter 3 transformed RAT from a research codebase into a maintainable, community-owned piece of scientific infrastructure.

The impact of this transition is evidenced by the download statistics reported in the chapter, with 70 to 80 percent of downloads originating from non-developer users. This is a meaningful indicator that the tool is reaching the practitioner community it was designed to serve. More importantly, the packaging effort created the forum and pipeline required for global, continuous improvement: new satellite missions such as SWOT can be incorporated, plugins for sediment trapping efficiency, rule curves, and water quality can be contributed, and errors discovered by users can be fed back into the codebase through a verifiable pathway. Chapter 3's contribution is therefore to establish the sociotechnical conditions under which satellite-based reservoir monitoring can evolve as a genuine community enterprise rather than as a project dependent on any single research group.

7.4. Chapter 4: Closing the Global Sedimentation Data Gap (GRILSS)

Chapter 4 confronted what had long been the most binding constraint on global sedimentation research: the absence of an open, standardized, and traceable dataset of observed reservoir sedimentation. Previous compilations were fragmented across national surveys, non-public

ICOLD records, and localized studies; they were heavily skewed toward the United States, inconsistent in their units and metrics, and rarely accompanied by the reservoir attributes needed for comparative analysis. GRILSS, the Global Reservoir Inventory of Lost Storage from Sedimentation, was assembled precisely to close this gap.

GRILSS compiles observed sedimentation records for 1,013 reservoirs spanning 75 major river basins and 54 countries, drawn from 143 traceable sources. It standardizes the reporting of sedimentation rate and capacity loss rate, documents the observation method and period for each record, and pairs each reservoir with harmonized attributes including built capacity, dam height, and catchment area. It is accompanied by vector data on reservoir and catchment geometries, making it immediately usable for spatial analysis. Initial exploration of the dataset revealed two patterns of immediate policy relevance: newer reservoirs appear to exhibit higher capacity loss rates than older ones, and basins such as the Paraná and the Yellow River emerge as global hotspots of sedimentation. GRILSS is therefore not only a resource; it is also a gateway for continued community curation, designed to be extended with multilingual sources and underrepresented smaller reservoirs as the global water community contributes.

7.5. Chapter 5: A Machine-Learning Framework for Global Sedimentation Estimation (RECLAIM)

Chapter 5 leveraged GRILSS to develop RECLAIM, a globally scalable machine-learning framework that estimates reservoir sedimentation from satellite-observable and globally available inputs. Using a dataset of 1,315 reservoirs and 88 predictor features spanning reservoir attributes, catchment characteristics, land cover, climate variables, and satellite-derived surface-area dynamics, Chapter 5 made three methodological contributions. First, it demonstrated that absolute sedimentation rate (SR) is a substantially more tractable predictand than capacity loss rate (CLR) for machine-learning estimation; CLR, although derived from SR, exhibits weak correlation with predictor features and with SR itself, because normalizing by reservoir capacity suppresses the catchment-driven sediment signal. Second, it produced the first data-driven global assessment of the physical drivers of sedimentation, showing that satellite-derived surface area, land cover, and catchment-scale sediment-transport proxies dominate SR, while reservoir operational and structural characteristics dominate CLR. Third, it delivered a dynamically weighted ensemble of

CatBoost, XGBoost, and LightGBM models that achieves an RMSE of 4.44 MCM/yr, MAE of 1.65 MCM/yr, and R^2 of 0.86 on held-out test data.

Importantly, although RECLAIM is trained with 88 features, it remains operationally usable with a substantially smaller subset, and feature engineering is automated within the framework. This design choice was deliberate: RECLAIM is intended not as a replacement for in-situ bathymetric surveys but as a rapid, cost-effective screening tool that identifies reservoirs most at risk of diminished storage capacity and therefore most in need of expensive ground-truth surveys or active sediment management. As Chapter 5 explicitly noted, RECLAIM was only feasible because RAT 3.0 provided the multi-decadal reservoir-operation tracking and GRILSS provided the calibration and validation data—an illustration of how the components of this dissertation depend on one another.

7.6. Chapter 6: A Global, Multi-Decadal Assessment of Reservoir Storage Loss (GLoRS)

Chapter 6 integrated the operational monitoring of RAT 3.0, the observational training data of GRILSS, and the estimation framework of RECLAIM into the first globally consistent, multi-decadal satellite-based assessment of reservoir sedimentation: the Global Long-term Reservoir Sedimentation (GLoRS) dataset, covering 1,412 reservoirs worldwide. The resulting picture is sobering. As of 2023, an estimated 88.4% of the installed storage capacity of these large reservoirs remains, implying that approximately 11.6% has already been lost to sedimentation. Storage is currently declining at an average rate of 0.42% per year, and the average large reservoir has lost nearly one-fifth of its original capacity.

Beyond these headline numbers, Chapter 6 established three structural insights that reframe how reservoir sedimentation should be understood. First, storage loss is scale-dependent in a way that cannot be inferred from reservoir size alone: large reservoirs accumulate the largest sediment volumes, but small reservoirs experience the fastest proportional depletion. Second, sedimentation is spatially organized rather than globally synchronized, clustering geographically according to basin sediment supply and hydroclimate. Third, climate variability—exemplified by the ENSO teleconnection—influences sedimentation primarily by amplifying extremes rather than by shifting mean deposition, so that changes in the variability of the hydroclimate may matter more for reservoir longevity than changes in its mean. The Three Gorges–Gezhouba cascade and the post-Wenchuan-earthquake response of the Zipingpu reservoir, analyzed as process-based case

studies, illustrate two distinct mechanisms—engineered hydraulic alteration and climate-modulated geomorphic disturbance—through which sediment regimes can be reorganized on decadal timescales.

Taken together, these findings reframe reservoir sedimentation: no longer a slow, background maintenance concern, but a measurable, climate-mediated constraint on global surface water storage that can now be tracked, year by year and basin by basin.

7.7. An Integrated Contribution

Viewed in aggregate, the five technical chapters of this dissertation constitute an end-to-end pipeline that did not previously exist: a satellite-based monitoring platform (RAT 3.0), its community-maintainable distribution (the RAT Python library), an open global training dataset of observed sedimentation (GRILSS), a globally scalable estimation framework (RECLAIM), and a globally consistent multi-decadal assessment of storage loss (GLoRS). Each component stands alone as a contribution to its respective subfield, but the whole is more than the sum of its parts. For the first time, a single question—how much reservoir storage remains on Earth, and how fast is it being lost?—can be answered consistently, reproducibly, and at planetary scale, with uncertainties that can be bounded and sources that can be traced.

Equally important is what this pipeline makes possible for others. By releasing the tools as open-source software, the data as open datasets, and the estimation framework as a transparent machine-learning model, this work lowers the barrier for water managers, policymakers, and researchers anywhere in the world to diagnose the sedimentation status of their own reservoirs and basins. In this sense, the dissertation's broader contribution is one of democratization: transforming reservoir sedimentation from a locally studied, data-limited problem accessible only to well-resourced institutions into a globally observable phenomenon that any stakeholder can engage with.

7.8. Future Recommendations

The tools, datasets, and findings presented in this dissertation open a number of research directions that should be pursued to advance the state of global reservoir and sedimentation science. The recommendations below are organized along four themes: strengthening the observational foundation, improving the estimation framework, deepening the process understanding, and extending the reach of the work into decision-making and adaptation.

7.8.1. Strengthening the Observational Foundation

The quality of every downstream result depends on the quality of the observations that feed it. Three priorities stand out. First, the integration of the Surface Water and Ocean Topography (SWOT) mission into RAT 3.0 should be pursued as a priority upgrade. SWOT provides simultaneous measurements of reservoir surface elevation, area, and storage change at unprecedented accuracy, and simulation studies already suggest it will substantially improve the fidelity of satellite-based reservoir monitoring. Second, the RAT architecture should be made more modular with respect to the choice of hydrological model and the ingestion of alternative satellite inputs, so that users can swap in basin-appropriate models and sensor streams without modifying the core code. Third, the GRILSS dataset should continue to be expanded, with particular emphasis on multilingual sources, small reservoirs (below 0.1 MCM), and underrepresented regions in Africa, Central and South Asia, and Latin America. Targeted field campaigns and partnerships with national water agencies will be needed to reduce the geographic bias that currently affects global training data.

7.8.2. Improving the Estimation Framework

RECLAIM demonstrates that absolute sedimentation rate can be estimated reliably from globally available inputs, but several methodological extensions would increase its value. Regional recalibration and evaluation should be undertaken once GRILSS coverage permits, so that model performance and uncertainty can be quantified separately for each major hydroclimatic region. The framework should be extended to provide probabilistic rather than point predictions, enabling users to weigh sedimentation estimates alongside their uncertainty in water-resource decisions. Physically informed machine-learning approaches, which embed mass-balance or sediment-transport constraints into model training, deserve particular attention as a means of improving generalization to data-sparse regions. Finally, the development of reservoir-specific plugins—for sediment trapping efficiency, rule-curve inference, water-quality tracking, and sediment-flushing operations—will expand the range of management questions that the RAT/RECLAIM stack can address.

7.8.3. Deepening the Process Understanding

The findings of Chapter 6 raise several process-level questions that merit dedicated investigation. The observation that climate variability influences sedimentation primarily through extremes, rather than through mean deposition, implies that future work should explicitly model event-scale sediment transport and its relationship to high-magnitude precipitation and runoff events. The apparent tendency for newer reservoirs to exhibit higher capacity loss rates deserves closer causal scrutiny: is this an artifact of observation duration, a reflection of siting decisions for recently built reservoirs in more sediment-rich basins, or a genuine trend driven by land-use change and climate intensification? Coupling GLoRS with land-use, soil-erosion, and sediment-connectivity models would help disentangle these possibilities. The case studies of the Three Gorges–Gezhouba cascade and the post-earthquake Zipingpu reservoir also suggest that cascading infrastructure and geomorphic shocks deserve systematic global treatment, rather than case-by-case study, to understand how often and where such regime shifts occur.

7.8.4. Extending the Reach into Decision-Making and Adaptation

A central premise of this dissertation is that scientific tools become impactful only when they inform decisions. Three directions are particularly important. First, reservoir sedimentation should be explicitly incorporated into global and regional water-security assessments, climate-adaptation frameworks, and infrastructure-planning models that have historically assumed static installed capacity. The results of Chapter 6 show that this assumption materially overstates available storage. Second, GLoRS should be used to prioritize reservoirs for intervention—whether through sediment flushing, dredging, upstream watershed management, or dam heightening—by combining estimated storage-loss rates with measures of the downstream population and economic activity served by each reservoir. Third, the tools and datasets developed here should be translated into decision-support products tailored to the needs of specific user groups, including operators of transboundary river basins, national water authorities, and international financial institutions that invest in dam infrastructure. Capacity-building programs, regional training workshops, and sustained engagement with the Mekong River Commission, the Asian Disaster Preparedness Center, and similar organizations will be important to ensure that the infrastructure built by this dissertation is used, maintained, and improved by the communities it is intended to serve.

7.9. Closing Remarks

Reservoirs are among the most consequential engineering artifacts of the twentieth century, and sedimentation is the process by which they are slowly but inexorably undone. For most of their history, the rate of this undoing has been invisible at the scales that matter for global water security. This dissertation has shown that it no longer needs to be. With four decades of satellite Earth observations, an open community-maintained monitoring platform, a curated global sedimentation dataset, a scalable machine-learning estimation framework, and a globally consistent multi-decadal assessment, reservoir sedimentation has been brought into the domain of measurable, predictable, and manageable phenomena. What remains is the harder work: using this new visibility to make better decisions, to prioritize the reservoirs most at risk, and to build the next generation of water infrastructure with the foreknowledge that storage is not static. It is the hope of this work that the tools, datasets, and insights presented here will support that effort—and that, in doing so, they will contribute, in some small measure, to a more resilient and equitable future for global water security.

Chapter 8. References

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Chapter 9. Important Tools (Software & Datasets)

9.1. Reservoir Assessment Tool (RAT)

Web Application: <http://www.satellitedams.net>

Code Availability: <https://zenodo.org/record/8268138>

Data Availability on RAT 3.0 Global Database: <https://zenodo.org/record/8267708>

RAT 3.0 Documentation: <http://ratdocs.io>

User manual: https://depts.washington.edu/saswe/rat/user_manual/RAT-3.0_User_Manual.pdf

GitHub Repository: <https://github.com/UW-SASWE/RAT>

Conda Package: <https://anaconda.org/channels/conda-forge/packages/rat/overview>

9.2. Global Reservoir Inventory of Lost Storage by Sedimentation (GRILSS)

Dataset DOI: <https://doi.org/10.17605/OSF.IO/W4UG8>

GitHub Repository: <https://github.com/UW-SASWE/GRILSS>

Web Application: <https://uw-saswe.github.io/GRILSS/>

9.3. Reservoir Estimation of Capacity Loss using AI based Methods (RECLAIM)

Software Documentation: <https://reclaimio.readthedocs.io/en/latest/>

GitHub Repository: <https://github.com/UW-SASWE/RECLAIM>

Web Application: <https://f-hossain-3.ce.washington.edu/reclaim/estimator>

Data DOI: <https://doi.org/10.5281/zenodo.17230533>

Software DOI: <https://doi.org/10.5281/zenodo.17230884>

Python Package: <https://pypi.org/project/pyreclaim/0.6.0/>

9.4. Global Long-term Reservoir Sedimentation (GLoRS)

Data DOI: <https://doi.org/10.17605/OSF.IO/2KF3R>

Web Application: <https://f-hossain-3.ce.washington.edu/reclaim/>

GitHub Repository: <https://github.com/UW-SASWE/GLoRS>

Code DOI: <https://doi.org/10.5281/zenodo.22003973>

Chapter 10. Appendix of Chapter 3

10.1. RAT Configuration File

Below is the ‘.yaml’ configuration file used to run RAT for the Hidkal Dam, as described in Section 3.6. Users can modify the parameters, guided by the provided comments, to apply RAT to a different area. For more details, refer to https://rat-satellitedams.readthedocs.io/en/latest/Configuration/rat_config/.

```
GLOBAL:

# Steps to run

steps: [1,2,3,4,5,6,7,8,9,10,12,13,14]

# Project directory path

project_dir: /cheetah1/sanchit_global_rat/RAT/

# Data directory path

data_dir: /cheetah1/sanchit_global_rat/RAT/data_time_48worker

# Basin shapefile path

basin_shpfile:
/cheetah1/sanchit_global_rat/RAT/custom_data/Hidkal_Dam_RAT_Tutorial/River_Basin/Krishna_River_Basin.json

# Name of column with unique ID in basin_shpfile

basin_shpfile_column_dict: {id: MRBID}

# Path of Global Elevation GeoTIFF file

elevation_tif_file:
/cheetah1/sanchit_global_rat/RAT/global_data/global_elevation_data/World_e-Atlas-UCSD_SRTM30-plus_v8.tif

# Number of CPU cores to use

multiprocessing: 1

BASIN:

# Name of the region where RAT is applied

region_name: Karnataka
```



```
# Basin name used for saving data
basin_name: Krishna
# Basin ID mapped to the basin_shpfile
basin_id: 2312
spin_up: true
# Start date (YYYY-MM-DD)
start: 2019-01-01
# End date (YYYY-MM-DD)
end: 2019-12-31
```

METSIM:

```
# Path to Metsim's Python environment
metsim_env: /cheetah1/sanchit_global_rat/RAT/models/metsim
# Metsim parameter file path
metsim_param_file: /cheetah1/sanchit_global_rat/RAT/params/metsim/params.yaml
```

VIC:

```
# Path to VIC's Python environment
vic_env: /cheetah1/sanchit_global_rat/RAT/models/vic
# VIC parameter file path
vic_param_file: /cheetah1/sanchit_global_rat/RAT/params/vic/vic_params.txt
vic_global_data: true
# VIC global parameter directory
vic_global_param_dir: /cheetah1/sanchit_global_rat/RAT/global_data/global_vic_params
# VIC soil parameter file for the continent
vic_basin_continent_param_filename: eurasia_params.nc
# VIC domain parameter file for the continent
vic_basin_continent_domain_filename: eurasia_domain.nc
```

ROUTING:

```

# Path to routing model
route_model: /cheetah1/sanchit_global_rat/RAT/models/routing/rout

# Routing parameter file
route_param_file: /cheetah1/sanchit_global_rat/RAT/params/routing/route_param.txt

# Global Flow Direction file
global_flow_dir_tif_file:
/cheetah1/sanchit_global_rat/RAT/global_data/global_drt_flow_file/global_drt_flow_16th
.tif

replace_flow_directions:
    {1: 3, 4: 5, 2: 4, 8: 6, 16: 7, 32: 8, 64: 1, 128: 2, 255: 0}

station_global_data: true

# Dam shapefile path
stations_vector_file:
/cheetah1/sanchit_global_rat/RAT/custom_data/Hidkal_Dam_RAT_Tutorial/Dam/Hidkal_Dam.js
on

# Column names for ID, name, longitude, and latitude in stations_vector_file
stations_vector_file_columns_dict:
    {id_column: GRAND_ID, name_column: DAM_NAME, lon_column: LONG_DD, lat_column:
LAT_DD}

ROUTING PARAMETERS:

# Unit hydrograph file path
uh: /cheetah1/sanchit_global_rat/RAT/params/routing/uh.txt

GEE:

# Reservoir shapefile path
reservoir_vector_file:
/cheetah1/sanchit_global_rat/RAT/custom_data/Hidkal_Dam_RAT_Tutorial/Dam/Hidkal_Reserv
oir.json

# Column names for ID, dam name, and area in reservoir_vector_file
reservoir_vector_file_columns_dict:
    {id_column: GRAND_ID, dam_name_column: DAM_NAME, area_column: AREA_SKM}

```

CONFIDENTIAL:

Path to secrets file

secrets:

/cheetah1/sanchit_global_rat/RAT/extras/confidential/data_download/secrets.ini

Chapter 11. Appendix of Chapter 5

11.1. Treatment of Missing Values

Dam height (HGT, Table 5.3) had the highest proportion of missing values in GRILSS. Out of 1,368 reservoirs, 159 (11.6%) lacked HGT information. The next highest count of missing values for any other variable was 66 (4.8%). This made HGT the most critical variable requiring special treatment, particularly since dam height can strongly influence reservoir sedimentation by reflecting how deep a reservoir is.

To approximate reservoir depth, we defined a proxy variable, *cap_area_ratio* (original built capacity (OBC, Table 5.3) divided by reservoir area (RA, Table 5.3)). A log–log relationship between *cap_area_ratio* (proxy for mean depth) and HGT was observed to be approximately linear, with a positive correlation of 0.6. Based on this relationship (Equation 9.1), a linear model was fitted to estimate missing HGT values (Figure 11.1a). For plausibility, estimates were constrained to lie between 5 m and 120 m. Because RA was not available for all reservoirs, even after this imputation step, 43 reservoirs still lacked HGT values.

$$\log_{10} HGT = 0.7 + 0.8 * \log_{10} \frac{OBC}{RA} \quad 9.1$$

To assess the extent of missing data, the number of missing variables was computed for each observation (Figure 11.1b). Many observations had 29–42 missing variables. To avoid introducing excessive noise from heavy imputation, all observations with ≥ 10 missing variables (53 in total) were excluded from further analysis. For the remaining observations, where fewer than 10 variables were missing, imputation was performed using the k-nearest neighbors (k-NN) method (Peterson, 2009) with $k = 5$, using the mean for continuous variables and the mode for categorical variables. After this step, the dataset comprised 1,315 observations with no missing values.

11.2. Sensitivity of Model Performance to Data Splitting

To assess the robustness of model performance to data partitioning, we conducted a random 10-fold group-based cross-validation analysis on the combined train and validation set (90% of dataset), ensuring that reservoirs remain exclusive across training and validation sets within each split. This approach preserves independence across reservoirs while enabling evaluation of model stability under different data partitions. Performance variability and distributional consistency were evaluated using RMSE, MAE, Kolmogorov–Smirnov (KS) statistic (Massey, 1951), and Wasserstein distance (Villani, 2009).

Figure 11.2 summarizes the variability in prediction performance and target distribution across the 10 splits. Panel (a) shows that model performance is generally consistent across splits, with mean RMSE = 7.62 ± 4.86 MCM/year and MAE = 3.13 ± 1.66 MCM/year. While some splits (e.g., Split 1 and Split 3) exhibit higher errors, these correspond to folds where high sedimentation rate (SR) reservoirs are present in the validation set. In contrast, splits with lower errors (e.g., Split 6 and Split 9) contain fewer extreme SR values. This indicates that variability in performance is primarily driven by the skewed and heavy-tailed distribution of SR, rather than instability in the model itself.

Panel (b) evaluates the representativeness of validation sets relative to training data using distributional metrics. The mean KS statistic (0.15) suggests only modest differences between empirical distributions, while the mean Wasserstein distance (3.81 MCM/year) indicates limited overall shift in sedimentation rates between training and validation sets. Although certain splits (e.g., Split 1) exhibit higher divergence—particularly in the upper percentiles—this is consistent with the sparse occurrence of extreme SR values rather than systematic bias in the splitting procedure.

Panel (c) further illustrates the composition of validation sets across sedimentation regimes. Most splits are dominated by low SR values (0–5 MCM/year), reflecting the global distribution of sedimentation rates. Higher SR categories (>20 MCM/year) are infrequently represented and unevenly distributed across folds. This uneven representation explains the observed variability in performance metrics and highlights the inherent challenge of modeling rare high-impact sedimentation events. Overall, these results demonstrate that RECLAIM exhibits stable predictive performance across multiple data partitions, and that observed variability is largely attributable to the natural distribution of sedimentation rates rather than sensitivity to a particular data split.

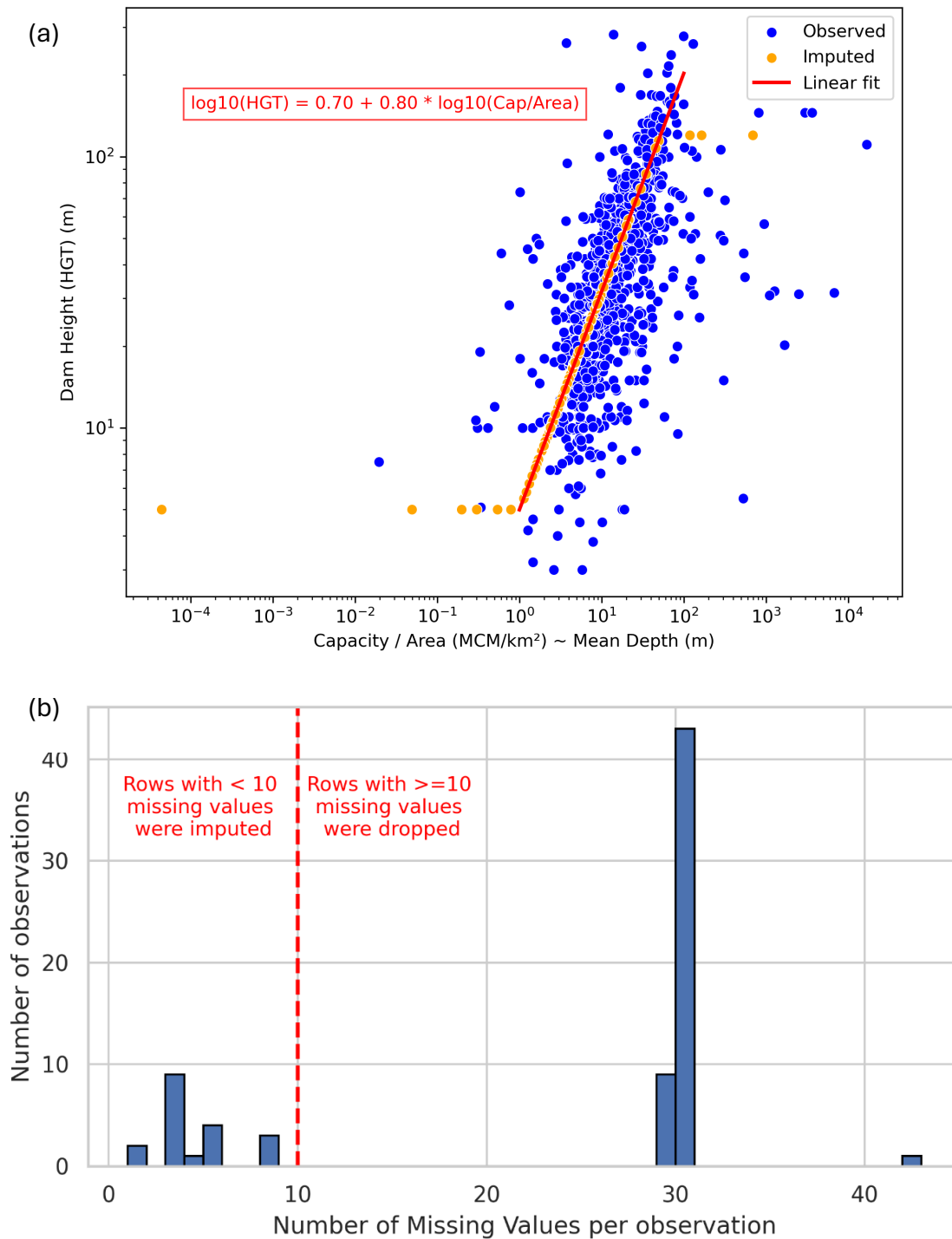


Figure 11.1 **(a)** Imputation of missing Dam Height values using a linear regression fit between dam height and the ratio of reservoir capacity to area on a log–log scale. **(b)** Distribution of missing values across observations.

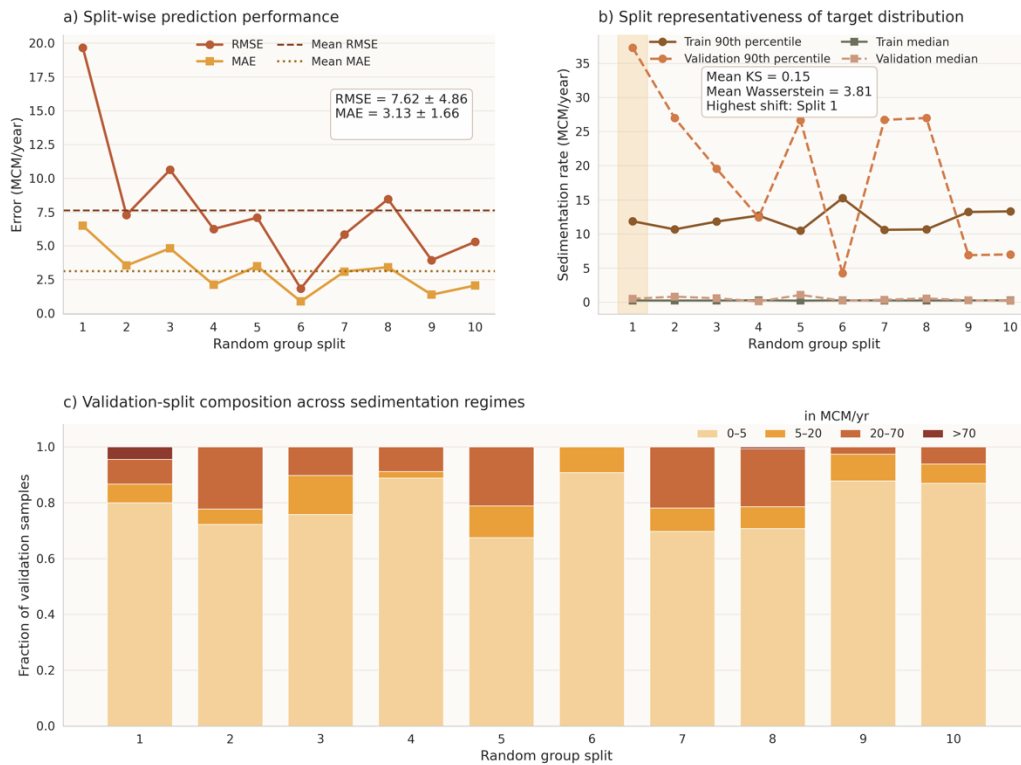


Figure 11.2 Stability and representativeness of model performance across group-based splits. (a) Prediction performance (RMSE and MAE) across random 10 group-based splits, with dashed lines indicating mean values. (b) Comparison of training and validation distributions using median and 90th percentile values, along with Kolmogorov–Smirnov (KS) statistic and Wasserstein distance as measures of distributional similarity. (c) Composition of validation sets across sedimentation rate regimes, showing variability in representation of high sedimentation cases due to the skewed distribution of SR.

Table 11.1 Description of catchment attributes derived from the *Global Land Cover-SHARE* dataset (FAO, 2014).

No.	Name	Abbreviation	Description	Units
-----	------	--------------	-------------	-------

P14	Land cover of artificial surfaces	LCAS	Percentage of catchment area of the reservoir covered by artificial surfaces.	%
P15	Land cover of cropland	LCC	Percentage of catchment area of the reservoir covered by cropland.	%
P16	Land cover of grassland	LCG	Percentage of catchment area of the reservoir covered by grassland.	%
P17	Land cover of trees	LCT	Percentage of catchment area of the reservoir covered by dense trees.	%
P18	Land cover of shrubs	LCS	Percentage of catchment area of the reservoir covered by shrubs.	%
P19	Land cover of herbaceous vegetation	LCHV	Percentage of catchment area of the reservoir covered by herbaceous vegetation.	%
P20	Land cover of mangroves	LCM	Percentage of catchment area of the reservoir covered by mangroves.	%
P21	Land cover of sparse vegetation	LCSV	Percentage of catchment area of the reservoir covered by sparse vegetation.	%
P22	Land cover of bare soil	LCBS	Percentage of catchment area of the reservoir covered by bare soil.	%
P23	Land cover of snow and glaciers	LCSG	Percentage of catchment area of the reservoir covered by snow and glaciers.	%
P24	Land cover of water bodies	LCWB	Percentage of catchment area of the reservoir covered by water bodies.	%
P25	Dominant Land cover	DLC	Dominant land cover type in the catchment of the reservoir from one of the above land cover types.	-

Table 11.2 Description of catchment attributes derived from the *SRTM30_Plus* dataset (Becker et al., 2009). “DL” stands for dimensionless unit.

No.	Name	Abbreviation	Description	Units
P31	Elevation	ELEV	Mean elevation of the catchment above sea level.	meter
P32	Slope	SLOP	Mean ground slope within the catchment.	degrees
P33	Curvature	CURV	Mean surface curvature of the terrain in the catchment, indicating concavity or convexity.	DL
P34	Aspect	ASP	Mean orientation of slopes within the catchment, measured clockwise from north.	degrees
P35	Hillshade	HILL	Mean relative illumination of the terrain surface in the catchment based on a hypothetical light source.	-

Table 11.3 Description of reservoir dynamics related time-series based features. OSY and OEY defines the observed sedimentation period and are mentioned in table 2.2. 'DL' stands for dimensionless units.

No.	Name	Abbreviation	Time-Series	Description	Units
P36	Mean Annual Inflow	MAI	Inflow (OSY-OEY)	Mean of annual inflows.	m ³ /s
P37	Peak Annual Inflow	PAI		Maximum annual inflow.	m ³ /s
P38	Coefficient of Variation in Inflow	I_cv		Mean ratio of the annual standard deviation to the annual mean of inflow.	DL
P39	Standard Deviation in Inflow	I_std		Mean of annual standard deviation of inflow.	m ³ /s
P40	Days with above 90 percentile inflow	I_above_90		Number of days in a year with inflow exceeding the 90th percentile threshold.	-
P41	Maximum annual persistence in inflow	I_max_persis		Maximum of annual decorrelation time across all years	days
P42	Mean Annual Outflow	MAO	Outflow (OSY-OEY)	Mean of annual outflows.	m ³ /s
P43	Standard Deviation in Outflow	O_std		Mean of annual standard deviation of outflow.	m ³ /s
P44	Coefficient of Variation in Outflow	O_cv		Mean ratio of the annual standard deviation to the annual mean of outflow.	DL
P45	Mean Evaporation	E_mean	Evaporation (OSY-OEY)	Mean evaporation rate.	mm/day
P46	Standard Deviation of Evaporation	E_std		Annual standard deviation of evaporation rate.	mm/day
P47	Mean Surface Area	SA_mean	Surface Area (1984-2023)	Mean of surface area.	km ²
P48	Standard Deviation of Surface Area	SA_std		Annual standard deviation of surface area.	km ²
P49	Coefficient of Variation in Surface Area	SA_cv		Mean ratio of the standard deviation to the mean of surface area.	DL
P50	Skewness of Surface Area	SA_skew		Mean skewness of surface area distribution	DL
P51	Kurtosis of Surface Area	SA_kurt		Mean kurtosis of surface area distribution	DL
P52	Mean Surface Area (clipped)	SA_mean_clip	Surface Area (OSY-OEY)	Mean of surface area.	km ²

P53	Days with above 90 percentile surface area	SA_above_90		Number of days in a year with surface area exceeding the 90th percentile threshold.	-
P54	Mean NSSC1	NSSC1_mean	NSSC1 (OSY-OEY)	Mean NSSC1.	DL
P55	Standard Deviation of NSSC1	NSSC1_std		Annual standard deviation of NSSC1.	DL
P56	Coefficient of Variation in NSSC1	NSSC1_cv		Mean ratio of the standard deviation to the mean of NSSC1.	DL
P57	Skewness of NSSC1	NSSC1_skew		Mean skewness of NSSC1 distribution.	DL
P58	Kurtosis of NSSC1	NSSC1_kurt		Mean kurtosis of NSSC1 distribution.	DL
P59	Mean NSSC2	NSSC2_mean	NSSC2 (OSY-OEY)	Mean NSSC2.	DL
P60	Days with above 90 percentile inflow	NSSC2_above_90		Number of days in a year with NSSC2 exceeding the 90th percentile threshold.	DL
P61	Maximum annual persistence in inflow	NSSC2_max_persis		Maximum of annual decorrelation time across all years	DL

Table 11.4 Description of features based on catchment dynamics related to land use and land cover derived from the *HILDA+ (HIStoric Land Dynamics Assessment+)* dataset (Winkler et al., 2021).

No.	Name	Abbreviation	Description	Units
D5	Vegetation Gain Frequency	VGF	Mean frequency of vegetation gain in the reservoir catchment during 1960-2019.	-
D6	Vegetation Loss Frequency	VLf	Mean frequency of vegetation loss in the reservoir catchment during 1960-2019.	-

Table 11.5 Description of features based on catchment dynamics related to meteorology derived using Reservoir Assessment Tool (Minocha et al., 2025). OSY and OEY defines the observed sedimentation period and are mentioned in table 2.2. 'DL' stands for dimensionless units.

No.	Name	Abbreviation	Time-Series	Description	Units
P62	Mean Annual Rainfall	MAR	Precipitation (OSY-OEY)	Mean annual rainfall during observation period.	mm/year

P63	Rainy days with 10 mm or more	#_rain_above_10		Number of days in a year with more than 10 mm rainfall.	-
P64	Rainy days with 50 mm or more	#_rain_above_50		Number of days in a year with more than 50 mm rainfall.	-
P65	Rainy days with 100 mm or more	#_rain_above_100		Number of days in a year with more than 100 mm rainfall.	-
P66	Mean Minimum Temperature	tmin_mean	Minimum Temperature (OSY-OEY)	Mean of minimum temperature.	°C
P67	Mean Maximum Temperature	tmax_mean	Maximum Temperature (OSY-OEY)	Mean of maximum temperature.	°C
P68	Mean Wind Speed	wind_mean	Wind Speed (OSY-OEY)	Mean wind speed.	m/s
P69	Standard Deviation of Wind Speed	wind_std		Annual standard deviation of wind speed.	m/s
P70	Coefficient of Variation in Wind Speed	wind_cv		Mean ratio of the standard deviation to the mean of wind speed.	DL
P71	Skewness of Wind Speed	wind_skew		Mean skewness of wind speed distribution.	DL
P72	Kurtosis of Wind Speed	wind_kurt		Mean kurtosis of wind speed distribution.	DL

Table 11.6 List of features derived through feature engineering. For features originating from Table 11.1, the original feature numbers and abbreviations are retained, with the land cover representation changed from percentage to absolute area. “DL” units stand for dimensionless.

No.	Name	Abbreviation	Definition/Formula	Reference Table	Units
P14	Land cover of artificial surfaces	LCAS	$= LCAS\% * CA$	Table 11.1	km ²
P15	Land cover of cropland	LCC	$= LCC\% * CA$	Table 11.1	km ²
P16	Land cover of grassland	LCG	$= LCG\% * CA$	Table 11.1	km ²
P17	Land cover of trees	LCT	$= LCT\% * CA$	Table 11.1	km ²
P18	Land cover of shrubs	LCS	$= LCS\% * CA$	Table 11.1	km ²

P19	Land cover of herbaceous vegetation	LCHV	$= LCHV\% * CA$	Table 11.1	km ²
P20	Land cover of mangroves	LCM	$= LCM\% * CA$	Table 11.1	km ²
P21	Land cover of sparse vegetation	LCSV	$= LCSV\% * CA$	Table 11.1	km ²
P22	Land cover of bare soil	LCBS	$= LCBS\% * CA$	Table 11.1	km ²
P23	Land cover of snow and glaciers	LCSG	$= LCSG\% * CA$	Table 11.1	km ²
P24	Land cover of water bodies	LCWB	$= LCWB\% * CA$	Table 11.1	km ²
P73	Age at observation end	AGE	$= OEY - BY$	Tables 5.2 and 5.3.	-
P74	Relative original capacity	ROBC	$= \frac{OBC}{CA}$	Table 5.3	m
P75	Geometry complexity	GC	$= \frac{RA}{RP^2}$	Table 5.3	DL
P76	Net vegetation gain frequency	NVGF	$= VGF - VLF$	Table 11.4	-
P77	Ratio tree cover to bare soil	R_tree_bare	$= \frac{LCT}{LCBS}$	Table 11.1	DL
P78	Ratio shrubs to bare soil	R_shrub_bare	$= \frac{LCS}{LCBS}$	Table 11.1	DL
P79	Ratio coarse to sand	R_coarse_sand	$= \frac{COAR}{SAND}$	Table 5.5	DL
P80	Relative mean annual surface area	rel_SA_mean_clip	$= \frac{SA_{mean_clip}}{RA}$	Tables 9.3 and 5.3	DL
P81	Ratio surface area to capacity	R_SA_cap	$= \frac{SA_{mean_clip}}{OBC}$	Tables 9.3 and 5.3	m ⁻¹
P82	Rainfall per unit area	rain_per_area	$= \frac{MAR}{CA}$	Tables 9.5 and 5.3	mm/km ²
P83	Trapping efficiency	TE	$= 100 * e^{-0.0079(\frac{MAI*3600*24*365}{OBC*1e6})}$	Table 5.3	%
P84	Residence time	RT	$= \frac{OBC * 1e6}{MAI * 3600 * 24 * 365}$	Table 5.3	years
P85	Estimated capacity loss rate	ECLR	$= TE * \frac{NSSC2_{mean}}{RT}$	Table 11.3 and 9.6	%/year

P86	Estimated sedimentation rate	ESR	$= \frac{ECLR * OBC}{100}$	Tables 9.6 and 5.3	million cubic meter/year
P87	Sediment influx	SIN	$= MAI * NSSC2_mean$	Table 11.3	m ³ /s
P88	Sediment outflux	SOUT	$= MAO * NSSC2_mean$	Table 11.3	m ³ /s

Table 11.7 List of features transformed using the natural logarithm. Original feature numbers have been retained and abbreviations have been prefixed with ‘log_’ to ensure consistency across the dataset.

No.	Name	Abbreviation	Reference Table
P1	Original Built Capacity	log_OBC	Table 5.3
P2	Dam Height	log_HGT	Table 5.3
P6	Reservoir Area	log_RA	Table 5.3
P7	Reservoir Perimeter	log_RP	Table 5.3
P8	Flow Length	log_FL	Table 5.3
P9	Catchment Area	log_CA	Table 5.3
P10	Differential Catchment area	log_DCA	Table 5.3
P14	Land cover of artificial surfaces	log_LCAS	Table 11.6
P15	Land cover of cropland	log_LCC	Table 11.6
P16	Land cover of grassland	log_LCG	Table 11.6
P17	Land cover of trees	log_LCT	Table 11.6
P18	Land cover of shrubs	log_LCS	Table 11.6
P19	Land cover of herbaceous vegetation	log_LCHV	Table 11.6
P20	Land cover of mangroves	log_LCM	Table 11.6
P21	Land cover of sparse vegetation	log_LCSV	Table 11.6
P22	Land cover of bare soil	log_LCBS	Table 11.6
P23	Land cover of snow and glaciers	log_LCSG	Table 11.6
P24	Land cover of water bodies	log_LCWB	Table 11.6
P36	Mean Annual Inflow	log_MAI	Table 11.3
P37	Peak Annual Inflow	log_PAI	Table 11.3
P39	Standard Deviation in Inflow	log_I_std	Table 11.3
P42	Mean Annual Outflow	log_MAO	Table 11.3
P43	Standard Deviation in Outflow	log_O_std	Table 11.3
P47	Mean Surface Area	log_SA_mean	Table 11.3
P48	Standard Deviation of Surface Area	log_SA_std	Table 11.3
P51	Kurtosis of Surface Area	log_SA_kurt	Table 11.3
P52	Mean Surface Area (clipped)	log_SA_mean_clip	Table 11.3
P62	Mean Annual Rainfall	log_MAR	Table 11.5
P74	Relative original capacity	log_ROBC	Table 11.6
P75	Geometry complexity	log_GC	Table 11.6
P80	Relative mean annual surface area	log_rel_SA_mean_clip	Table 11.6
P81	Ratio surface area to capacity	log_R_SA_cap	Table 11.6
P82	Rainfall per unit area	log_rain_per_area	Table 11.6
P83	Trapping efficiency	log_TE	Table 11.6

P84	Residence time	log RT	Table 11.6
P85	Estimated capacity loss rate	log ECLR	Table 11.6
P87	Sediment influx	log SIN	Table 11.6
P88	Sediment outflux	log SOUT	Table 11.6

Table 11.8 Effect of loss functions on CLR regression performance

Model	Loss Function	RMSE (Test)	MAE (Test)	R ² (Test)
XGBoost	Squared Error	1.83	0.87	0.27
	Tweedie	1.92	0.81	0.20
LightGBM	Regression	1.96	1.06	0.16
	Tweedie	1.93	0.82	0.19
CatBoost	RMSE	1.83	0.82	0.27
	Huber	2.06	0.81	0.08

Table 11.9 Definition and enumeration of predictor feature categories used in RECLAIM.

All 88 input features are grouped into ten thematic categories based on their physical or data-source characteristics.

Category	Description	Features (Abbreviations)
Catchment Characteristics	Topographic and morphological attributes of the upstream catchment area	CA, DCA, ASP, HILL, CURV, ELEV, SLOP
Land Cover / Land Use	Fractional land cover classes and vegetation indices derived from remote sensing	LCM, LCWB, LCG, LCC, LCS, LCBS, LCT, LCAS, LCSV, LCHV, R_shrub_bare, R_tree_bare, DLC, NVGF, LCSG
Reservoir Characteristics	Static geometric and design attributes of the reservoir and dam structure	RA, RP, FL, GC, AECC, AECS, AECL, HGT, OBC, ROBC, AGE
Satellite Observations	Annual distribution statistics of reservoir surface area and Normalized Suspended Sediment Concentration (NSSC) derived from multi-decadal satellite imagery	R_SA_cap, SA_mean_clip, SA_std, rel_SA_mean_clip, SA_skew, SA_mean, SA_kurt, SA_cv, SA_above_90, NSSC1_mean, NSSC1_std, NSSC1_cv, NSSC1_skew, NSSC1_kurt, NSSC2_mean, NSSC2_max_persis, NSSC2_above_90
Derived Physical Quantities	Physically derived indices including trap efficiency,	TE, RT, ESR, SOUT, SIN, ECLR

	residence time, and estimated capacity metrics	
Reservoir Operations	Annual distribution statistics of reservoir inflow and outflow	MAI, I_std, O_cv, MAO, O_std, I_max_persis, I_above_90, PAI, I_cv
Sediment Type	Soil texture and sediment composition attributes of the upstream catchment	BULK, SILT, SAND, CLAY, R_coarse_sand, COAR
Climate & Rainfall	Long-term annual averages and rainfall intensity statistics for the catchment	rain_per_area, MAR, tmax_mean, tmin_mean, E_mean, E_std, #_rain_above_10, #_rain_above_50, #_rain_above_100
Wind	Annual wind speed distributional statistics for the reservoir location	wind_mean, wind_std, wind_skew, wind_kurt, wind_cv
Dam Location	Geographic coordinates and major river basin identifier	LAT, LON, MRB

Table 11.10 Sensitivity of RECLAIM predictions to the removal of individual predictors (top 20). Each predictor is omitted one at a time, and the resulting changes in model performance are quantified using Δ RMSE and Δ MAE (MCM/year). Additional columns summarize the absolute change in predicted sedimentation rate (SR) across all reservoirs in test set using mean, median, and maximum values.

Predictor	Δ RMSE (MCM/year)	Δ MAE (MCM/year)	Mean change in predicted SR (MCM/year)	Median change (MCM/year)	Maximum change (MCM/year)
OBC	3.642	1.842	2.715	0.744	32.493
rain_per_area	2.387	4.178	5.347	4.812	15.465
LCWB	0.590	0.196	0.575	0.018	14.142
CA	0.541	0.118	0.663	0.014	12.295
LCS	0.526	0.104	0.621	0.017	12.189
LON	0.411	0.087	0.598	0.024	7.681
LCC	0.409	0.138	0.507	0.015	6.718
AECC	0.377	1.100	1.434	0.771	4.483
I_above_90	0.340	0.068	0.281	0.056	10.245
log R SA_cap	0.258	0.355	0.784	0.545	8.905
wind_cv	0.234	0.717	1.200	0.915	6.054
NSSC1_std	0.193	0.011	0.201	0.003	5.745
LCG	0.185	0.100	0.415	0.048	6.886
SA_mean_clip	0.168	0.020	0.323	0.003	4.946
E_std	0.123	0.035	0.223	0.017	1.857
SA_std	0.120	0.042	0.163	0.024	2.873
DCA	0.115	0.039	0.186	0.018	1.596
SA_mean	0.092	-0.012	0.126	0.008	2.873

NSSC1 mean	0.066	0.018	0.080	0.009	1.141
R shrub bare	0.062	0.018	0.206	0.019	3.283

Chapter 12. Appendix of Chapter 6

Table 12.1 Input variables used by RECLAIM to estimate annual reservoir sedimentation (MCM yr⁻¹). TS denotes time-series inputs and DL denotes dimensionless variables.

S. No.	Input	Description	Units
1.	Build Year	Year of dam completion	-
2.	Major River Basin	River basin in which the reservoir is located	-
3.	Dam Latitude	Latitude of dam location	Degrees
4.	Dam Longitude	Longitude of dam location	Degrees
5.	Original Built Capacity	Design storage capacity at time of construction	MCM
6.	Dam Height	Structural height of the dam	m
7.	Reservoir Bathymetry	Elevation–area relationship of the reservoir	m, km ²
8.	Reservoir Geometry	Spatial extent of the reservoir footprint	-
9.	Catchment Geometry	Spatial extent of the contributing drainage area	-
10.	Catchment Area	Total upstream drainage area	km ²
11.	Differential Catchment Area	Effective drainage area after accounting for upstream regulation	km ²
12.	Inflow TS	Time series of reservoir inflow	m ³ /day
13.	Outflow TS	Time series of reservoir outflow	m ³ /day
14.	Surface Area TS	Time series of reservoir surface area	km ²
15.	Evaporation TS	Time series of evaporation over reservoir surface	mm
16.	NSSC 1 TS	Normalized suspended sediment concentration proxy (variant 1: near infrared/red band)	DL
17.	NSSC 2 TS	Normalized suspended sediment concentration proxy (variant 2: red/green band)	DL
18.	Precipitation TS	Catchment-averaged precipitation time series	mm
19.	Temperature (Min & Max) TS	Catchment-averaged minimum and maximum air temperature	°C
20.	Wind Speed TS	Catchment-averaged wind speed	m/s

Table 12.2 Data products used by the Reservoir Assessment Tool (RAT 3.0) to derive time-varying reservoir and catchment inputs for RECLAIM. This table is adapted from Tables 6 and 7 in Minocha et al. (2025d). DL denotes dimensionless variables.

Time-Series	Data Products used by RAT	Frequency	Duration	Units
Inflow	ERA-5 reanalysis (Hersbach et al., 2020); NCEP/NCAR (Kalnay et al., 1996)	Daily	1984-2023	m ³ /day

Outflow	Mass balance approach	4-16 days	1984-2023	m ³ /day
Surface Area	Landsat 5,7,8 and 9; Sentinel 2; Sentinel 1	4-16 days	1984-2023	km ²
Evaporation	NCEP/NCAR reanalysis (Kalnay et al., 1996)	Daily	1984-2023	mm
NSSC1 (near-infrared/red band)	Landsat 5,7,8 and 9; Sentinel 2; Sentinel 1	8-16 days	1984-2023	DL
NSSC2 (red/green band)	Landsat 5,7,8 and 9; Sentinel 2; Sentinel 1	8-16 days	1984-2023	DL
Precipitation	ERA-5 reanalysis (Hersbach et al., 2020)	Daily	1984-2023	mm
Minimum Temperature	NCEP/NCAR reanalysis (Kalnay et al., 1996)	daily	1984-2023	°C
Maximum Temperature	NCEP/NCAR reanalysis (Kalnay et al., 1996)	Daily	1984-2023	°C
Wind Speed	NCEP/NCAR reanalysis (Kalnay et al., 1996)	Daily	1984-2023	m/s

12.1. Model Performance and Uncertainty by Reservoir Size

RECLAIM's predictive skill varies systematically across the reservoir-size distribution, and this scale dependence is important for interpreting the model's uncertainty. We therefore stratified model performance into five reservoir-size classes (<1 MCM, 1–10 MCM, 10–100 MCM, 100–1,000 MCM, and ≥1,000 MCM) and evaluated R², RMSE, MAE, relative RMSE (RRMSE; RMSE normalized by the class mean observed sedimentation rate), and mean bias error (MBE) for each class (Table 12.3 RECLAIM performance by reservoir size class. These are in-sample (training) diagnostics computed on the full model-development sample (n = 1,315 reservoir observations).). These statistics are in-sample diagnostics computed across the full model-

development dataset ($n = 1,315$ reservoir observations). Because the held-out sample is not sufficiently large to partition reliably into the same number of size classes, these results characterize how model performance changes with reservoir scale rather than its generalization to unseen reservoirs; the latter is assessed independently through the group-based cross-validation reported in Section 5.6.4.

The stratified results show a clear increase in relative error toward smaller reservoirs (Table 12.3 RECLAIM performance by reservoir size class. These are in-sample (training) diagnostics computed on the full model-development sample ($n = 1,315$ reservoir observations).). RRMSE is particularly large for reservoirs below 10 MCM, reflecting both the limited range of observed sedimentation rates within these classes and the resolution floor associated with predicting very small absolute rates. This pattern is consistent with the model's absolute-error training objective: an error that is small in absolute terms can nevertheless represent a large fraction of the observed sedimentation rate for small reservoirs. Accordingly, RRMSE provides a more informative basis for comparing performance across reservoir sizes than R^2 alone. The negative R^2 values for the <10 MCM classes arise from the restricted within-class variance rather than from exceptionally large absolute errors; for example, the <1 MCM class has an RMSE of only $0.369 \text{ MCM yr}^{-1}$. In contrast, predictive performance improves substantially with reservoir size, with the $\geq 1,000$ MCM class achieving $R^2 = 0.912$ and an RRMSE of 36.1%. This is particularly relevant to the study's principal conclusions because reservoirs exceeding 1 km^3 account for the majority of installed storage capacity in GLoRS, whereas reservoirs below this threshold account for less than 3% of total capacity. Thus, the scale dependence of prediction error has limited influence on the aggregate estimates emphasized here.

The bias diagnostics provide additional context for this trade-off across scales. MBE is small in absolute terms for the smaller reservoir classes and remains modest relative to the RMSE of the largest reservoirs. Importantly, the bias for the $\geq 1,000$ MCM class is slightly negative ($-1.491 \text{ MCM yr}^{-1}$), rather than positive, indicating that the higher predictive accuracy associated with large reservoirs does not arise from systematically inflating the sedimentation estimates on which the main conclusions depend. If anything, this small negative bias suggests a conservative tendency at the largest reservoir scale. We therefore treat the observed scale dependence as a

defined limitation of the framework rather than implying uniform predictive performance across all reservoir sizes.

These size-stratified diagnostics are complemented by the independent generalizability assessment reported in Section 5.6.4, which evaluated RECLAIM under a 10-fold group-based cross-validation design ensuring strict reservoir-level independence between training and validation data. In that analysis, each reservoir was assigned exclusively to either training or validation within a given fold, preventing any leakage of reservoir-specific information across splits and thereby providing a more robust estimate of out-of-sample performance. The cross-validation yielded $\text{RMSE} = 7.62 \pm 4.86 \text{ MCM yr}^{-1}$ and $\text{MAE} = 3.13 \pm 1.66 \text{ MCM yr}^{-1}$, where the reported bounds represent the standard deviation across the ten folds and thus quantify the sensitivity of model performance to the composition of the validation sets. This variability reflects the strongly skewed, heavy-tailed nature of sedimentation rates, whereby folds containing a higher proportion of large or high-sedimentation reservoirs exhibit correspondingly larger absolute errors.

Within the present study, however, the primary focus is not on aggregate generalization error but on how predictive uncertainty varies systematically with reservoir size. The stratified diagnostics therefore provide the central lens for interpretation, revealing how model performance degrades toward smaller reservoirs while remaining substantially more stable for large storage systems that dominate global capacity. In this context, the cross-validation results referenced above serve as an external benchmark of overall model generalizability, whereas the size-class analysis presented here explains the internal structure of that error across the reservoir population.

Table 12.3 RECLAIM performance by reservoir size class. These are in-sample (training) diagnostics computed on the full model-development sample ($n = 1,315$ reservoir observations).

Reservoir size class	N reservoirs	R²	RMSE (MCM yr⁻¹)	MAE (MCM yr⁻¹)	RRMSE (%)	MBE (MCM yr⁻¹)
<1 MCM	147	-3068.735	0.369	0.132	10,166.3	+0.071
1-<10 MCM	180	-5.957	0.280	0.147	473.0	+0.052
10-<100 MCM	392	0.482	0.458	0.198	145.8	+0.013
100-<1,000 MCM	354	0.733	1.581	0.876	75.8	-0.144

≥1,000 MCM	242	0.912	8.084	4.080	36.1	−1.491
All reservoirs	1,315	0.939	3.576	1.080	74.7	−0.294

12.2. Surface-Layer Optical Limitations and Predictor Sensitivity

Surface reflectance cannot directly resolve bedload transport along the channel floor or sediment held in subsurface density currents. This is a real constraint on NSSC1 and NSSC2 as standalone measurements. However, RECLAIM does not rely on NSSC1 and NSSC2 alone. They are two of twenty raw input variables, contributing roughly ten of RECLAIM's eighty-eight engineered features. The remaining inputs cover reservoir geometry, catchment characteristics, hydrology, and climate. RECLAIM's predictive skill comes from this combined set of physical drivers working together, not from optical retrieval alone.

The quantification of how much of total sediment transport is bedload versus suspended load varies across studies in the literature, depending on river type and catchment conditions. In general river systems, suspended load typically accounts for 85 to 99 percent of total clastic sediment load, with bedload making up the remaining 1 to 15 percent (Babinski, 2005). This partitioning is not uniform across river types, however. In gravel-bed rivers with large catchments, the bedload fraction is usually small, often close to 1 percent, while in sand-bed rivers the bedload fraction can be substantial, ranging from 30 to 50 percent, even in large catchments (Turowski et al., 2010). Where bedload is more important, RECLAIM's reliance on suspended-sediment proxies would tend to underestimate rather than overestimate total sedimentation, since a transport pathway is missed rather than double-counted. This is a bounded and directionally conservative limitation, not an unconstrained source of error.

Suspended sediment concentration and bedload transport share the same underlying drivers: catchment erosion, discharge, and slope. When suspended sediment concentration is high, bedload tends to be high as well, even though the two do not necessarily scale at the same rate. RECLAIM is trained across geomorphic, hydrological, and climate covariates together with NSSC, allowing it to learn this qualitative co-variation and use surface reflectance as one signal among many that together track total sediment transport, rather than as a direct volumetric measurement on its own.

NSSC1 and NSSC2 also differ in their susceptibility to confusion between suspended sediment and chlorophyll. NSSC2, a Red-over-Green ratio, is comparatively robust: sediment and chlorophyll affect it in opposite directions, since sediment raises Red reflectance while chlorophyll lowers it, and the two effects tend to cancel rather than combine into a false signal. NSSC1, a near-infrared-over-Red ratio, is more exposed to this confusion, since algal cell structure raises near-infrared reflectance while chlorophyll absorption lowers Red, which can partially mimic a sediment signature. This risk is bounded by the same design feature described above: NSSC1 and NSSC2 together make up a small share of RECLAIM's predictors, and the model weighs them alongside non-optical covariates, including catchment slope, land cover, seasonality, reservoir geometry, and climate zone.

A leave-one-out predictor sensitivity analysis (Figure 12.1) removes each predictor in turn and measures the resulting change in RMSE and MAE. Satellite-derived predictors as a group show limited sensitivity overall. The only optical feature to appear among the fifteen most influential predictors, the standard deviation of NSSC1, changes RMSE by 0.19 MCM/yr and MAE by 0.1 MCM/yr when removed, a small effect in absolute terms. This indicates that RECLAIM's combined predictive skill does not depend heavily on its optical inputs.

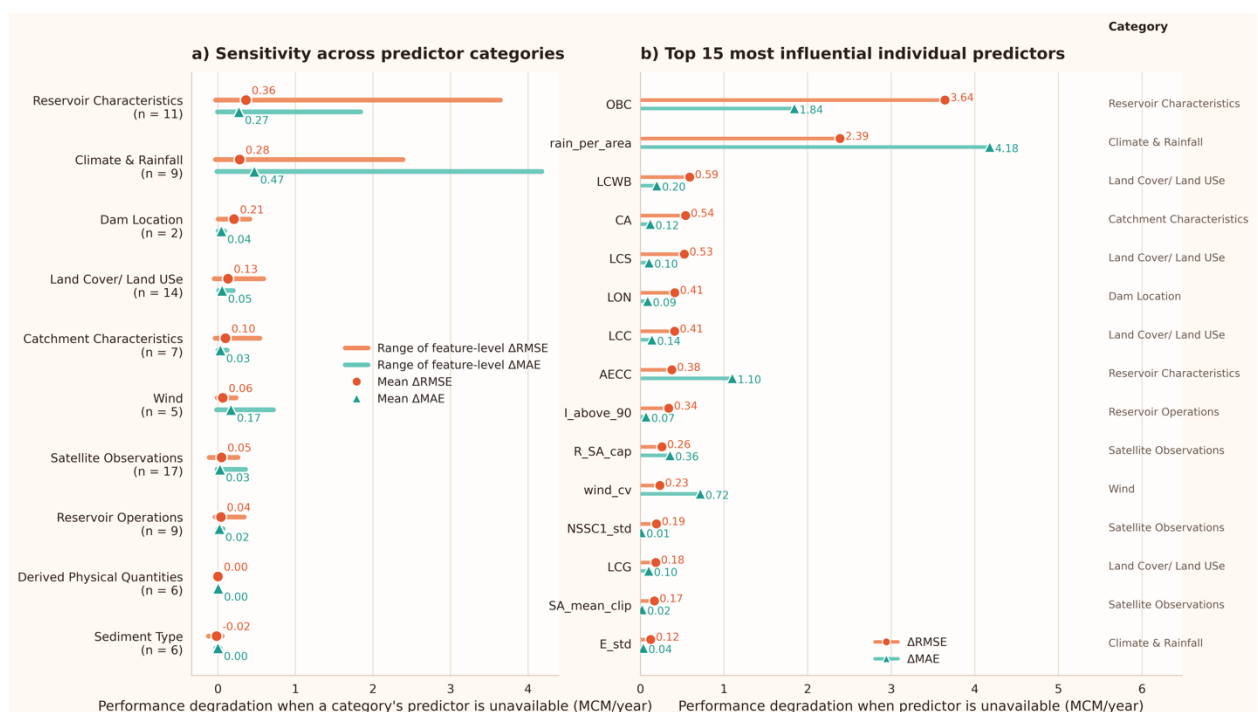


Figure 12.1 Leave-one-out predictor sensitivity analysis, reproduced from Figure 5.13 (see also Table 11.10). Bars show the change in RMSE and MAE (MCM yr^{-1}) resulting from removing each predictor individually; satellite-derived optical predictors (NSSC1, NSSC2) show limited sensitivity relative to non-optical covariates.

12.3. Scope Limitations

12.3.1. Rate-Only Architecture and Trap-Efficiency Decline

RECLAIM predicts annual sedimentation rates from reservoir and catchment observations for the year being predicted. It does not track the volume of sediment already deposited and therefore carries no memory of cumulative fill state. As a result, it does not represent the trap-efficiency decline described by Brune's curve, under which a reservoir that is substantially infilled traps a smaller fraction of incoming sediment than the same reservoir earlier in its operating life. The directional consequence is overestimation: annual rates for reservoirs in advanced stages of filling are more likely to be overestimated than underestimated. Reservoir age, engineered from the Build Year input, is among RECLAIM's derived features and may serve as an indirect, partial proxy for this state dependence, since trap efficiency and sediment supply dynamics vary systematically over a reservoir's operating life. However, we treat this as a plausible contributing mechanism rather than a demonstrated one, as no feature-importance or partial-dependence analysis has isolated age's contribution, and it is unlikely to fully offset the bias. We present this as a defined scope limitation of a rate-only framework, not as an error in the underlying analysis. The design-capacity cap applied during aggregation guards against physically impossible cumulative states but is not a substitute for explicit state tracking.

12.3.2. Active Sediment Management Interventions

GLoRS v1.0 estimates gross, or potential, sedimentation in the absence of active management interventions such as dredging, flushing, and bypassing. Thus, net capacity in actively managed reservoirs will therefore be higher than reported here. This gap matters only where it is large enough to reshape the trends and conclusions we draw, so the relevant question is how widespread active management actually is. At the scale needed to materially alter capacity trends, that is, routine flushing, bypass tunneling, or engineered dredging programs, active management is concentrated in a relatively small number of heavily managed basins, notably parts of China,

Japan, Switzerland, and Taiwan. Its influence on our reported global trends is therefore regionally confined rather than systemic.

Even within those basins, RECLAIM is not blind to management effects by construction, even though management status is not an explicit input to the model. RECLAIM is trained against GRILSS, which includes reservoirs under active sedimentation management, and it draws on a broad set of physical covariates, including land cover change such as afforestation and shifts in upstream sediment supply, both of which are themselves altered by management interventions. Consistent with this, RECLAIM independently reproduces declining sedimentation-rate trends across Europe, the central United States, and northeastern China (Figure 6.11), a region that includes several actively managed basins such as the Yellow River system. This pattern suggests the model is picking up a management-correlated signal through its covariates rather than assuming a uniform, unmanaged accumulation rate everywhere; we present this as a plausible mechanism rather than a confirmed, formally isolated effect, since we have not run an ablation experiment removing management-correlated covariates to test it directly.

To bound the size of the remaining gap rather than leave it qualitative, we turn to documented cases of active sediment management. At the Genissiat Reservoir on the Rhône River, coordinated flushing every three years limited sediment accumulation to roughly 4.5 million tons over four decades, versus an estimated 23 million tons without intervention, a reduction of about 80% (Kondolf et al., 2014). Sediment bypass tunneling, the primary management technique in Japan, Switzerland, and Taiwan, has been reported to reduce sedimentation by up to 89% and prevent roughly 9% of storage loss per operating cycle in narrow reservoirs (Kondolf et al., 2014; Sumi et al., 2004). Comparable single-event and regional-scale evidence points in the same direction: a 2019 flushing event at Xiaolangdi Reservoir on the Yellow River recovered 4 to 5% of storage capacity in one operation (Yang et al., 2025), and the United States loses roughly 0.2% of reservoir capacity per year compared with roughly 2.3% per year in China, where sediment loads and active management coincide (Delang, 2018; Tan et al., 2019; Niu and Shah, 2021).

Taken together, these cases indicate that intensive management can offset roughly 50 to 80% of potential sedimentation, which implies GLoRS estimates in those specific basins could overstate net capacity loss by a factor of roughly two to five. We present this as a bounded, regional sensitivity confined to a defined set of heavily managed basins, not as a correction to our global

estimates or conclusions, which are drawn predominantly from reservoirs without comparable management intervention.

Both, the rate-only architecture's blindness to cumulative fill state and the absence of an explicit management input defines the scope within which GLoRS estimates should be interpreted, rather than indicating errors in the underlying analysis.

12.4. ENSO Classification Robustness

This section provides full methodological and statistical detail supporting the “ENSO Classification Robustness” subsection in Methods, testing whether the $|r| \geq 0.15$ threshold used to classify reservoirs as El Niño- or La Niña-dominated reflects a genuine population-level relationship rather than an artifact of autocorrelation or an arbitrary choice of cutoff.

Two composite curves are used throughout this section, matching Figure 6.10(e–f). The mean composite is the cross-reservoir average of the sedimentation-rate anomaly in a given year, computed separately for the El Niño-dominated and La Niña-dominated reservoir groups. The dominant-extreme composite is, for that same year and group, whichever of the 10th or 90th percentile sedimentation-rate anomaly across reservoirs has the larger magnitude (sign kept). The mean composite summarizes the group's typical behavior in a given year; the dominant-extreme composite summarizes its most extreme behavior.

12.4.1. Test 1: Composite-Amplification Test

What we tested: whether the dominant-extreme composite's sensitivity to ENSO forcing is larger than the mean composite's, i.e., whether ENSO amplifies extremes more than it shifts the mean. We regressed both composites against the annual Niño 3.4 anomaly and computed the slope-magnitude difference, $\Delta = |\text{slope of dominant-extreme composite}| - |\text{slope of mean composite}|$, testing significance via a moving-block bootstrap (Künsch, 1989; contiguous 4-year blocks, 5,000 resamples) that resamples years jointly across both composites, preserving each series' own year-to-year persistence.

Results: both composites are significantly correlated with Niño 3.4 (mean composite: $r = 0.62$, $p = 0.0002$ for El Niño-dominated; $r = -0.77$, $p < 0.0001$ for La Niña-dominated), but the dominant-extreme composite's slope is significantly larger in magnitude in both groups (El Niño-dominated:

$\Delta = 1.69 \text{ MCM yr}^{-1}$ per unit Niño 3.4 anomaly, 95% CI [0.67, 2.71]; La Niña-dominated: $\Delta = 1.64$, 95% CI [1.27, 2.00]; both exclude zero), corresponding to a 3.1-fold and 4.4-fold larger slope respectively (Figure 12.2a).

Interpretation: ENSO measurably shifts both the mean and the extremes of the sedimentation-anomaly distribution within these reservoir populations, but its effect is concentrated disproportionately in the tails — the precise, quantitative version of the “amplifies extremes, not means” pattern visible in Figure 6.10(e–f).

12.4.2. Test 2: Null-Permutation Test

What we tested: because both ENSO-dominance groups were themselves selected by their correlation with Niño 3.4, whether the amplification pattern in Test 1 is specific to these ENSO-classified groups or a generic property of aggregating anomalies across any similarly sized group of reservoirs. We built a null distribution by repeatedly (2,000 iterations) drawing random reservoir groups of matching size from the full pool of eligible large-infrastructure reservoirs, without reference to their ENSO correlation, and recomputed the same slope-magnitude difference for each random draw.

Results: none of the 2,000 randomly composed groups produced a slope-magnitude difference as large as the one observed in either ENSO-classified group (empirical $p < 0.001$ for both groups; Figure 12.2b).

Interpretation: the amplification pattern is not a generic consequence of pooling anomalies across many reservoirs. It is specific to the ENSO-classified populations, which is what would be expected if the classification captures a genuine physical response rather than an artifact of aggregation.

12.4.3. Test 3: Threshold-Sensitivity Sweep

What we tested: whether Tests 1 and 2 depend on the specific $|r| \geq 0.15$ cutoff used to build the classified groups, by repeating both tests at alternative thresholds ($|r| \geq 0.10, 0.20, 0.25, 0.30$), reclassifying reservoirs and rebuilding the composite curves and null distribution independently at each cutoff.

Results: both tests remained significant at every threshold tested, not only near 0.15 (bootstrap 95% CI on the slope-magnitude difference excludes zero; null-permutation $p \leq 0.0025$ throughout), and the amplification ratio stays within a similar $2.8\times\text{--}4.7\times$ band across the whole range (Table 12.4).

Interpretation: the $|r| \geq 0.15$ threshold is not a fragile or cherry-picked choice. The underlying amplification pattern holds across a broad range of plausible classification thresholds, which is the pattern expected from a real relationship rather than one that only appears where 0.15 happens to sit.

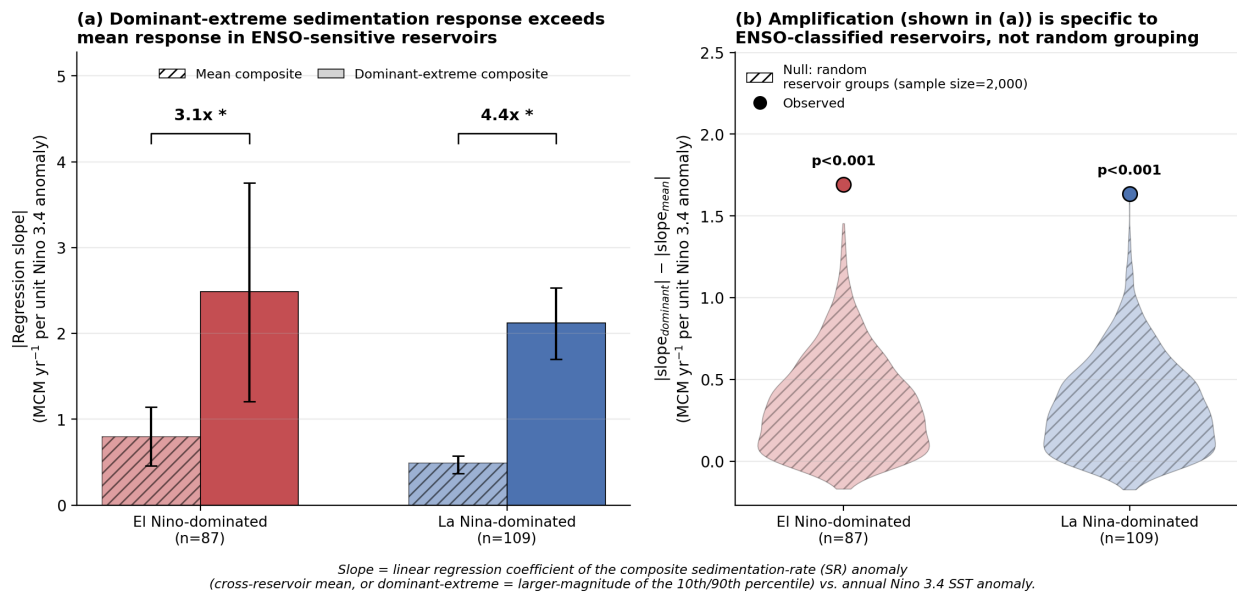


Figure 12.2 Composite mean vs. dominant-extreme amplification test at the $|r| \geq 0.15$ classification cutoff. (a) Grouped bars: |regression slope| of the mean composite vs. the dominant-extreme composite against Niño 3.4 anomaly, per ENSO group, with bootstrap 95% CI and the amplification ratio annotated. (b) Null-permutation distribution of the slope-magnitude difference from 2,000 randomly composed reservoir groups, with the observed group value marked.

Table 12.4 Composite-amplification and null-permutation test results recomputed across alternative $|r|$ classification thresholds. Slope-magnitude Δ is the difference between the

(absolute) regression slope of the dominant-extreme composite and that of the mean composite against Niño 3.4 anomaly ($\Delta = |\text{slope_dominant-extreme}| - |\text{slope_mean}|$); see Section 12.4 for full definitions.

 r cutoff	ENSO group	N	Slope-magnitude [95% CI]	Δ	Amplification ratio	Null- permutation p
0.10	El Niño- dominated	141	1.34 [0.31, 2.36]		3.04x	0.0005
0.10	La Niña- dominated	147	1.62 [1.22, 2.01]		4.72x	0.0005
0.15	El Niño- dominated	87	1.69 [0.67, 2.71]		3.13x	0.0005
0.15	La Niña- dominated	109	1.64 [1.27, 2.00]		4.36x	0.0005
0.20	El Niño- dominated	54	2.10 [1.03, 3.09]		3.12x	0.0005
0.20	La Niña- dominated	73	1.58 [1.22, 1.96]		3.82x	0.0015
0.25	El Niño- dominated	32	2.70 [1.42, 3.91]		3.11x	0.0005
0.25	La Niña- dominated	45	1.76 [1.49, 2.07]		3.63x	0.0015
0.30	El Niño- dominated	19	3.11 [1.16, 4.67]		2.84x	0.0005
0.30	La Niña- dominated	29	1.77 [1.32, 2.09]		3.08x	0.0025

12.5. Mechanistic Driver Attribution

This section provides full methodological and statistical detail supporting the “Mechanistic Drivers of Climate–Sedimentation Linkages” subsection in Methods, testing which physical pathways — natural climatic (delivery) or reservoir-operations (retention) — best explain sedimentation-rate variability at the level of individual reservoirs.

12.5.1. Data Sources

Candidate driver variables are drawn from sources beyond the existing GLoRS climate and hydrology fields. Precipitation (ERA-5 reanalysis; Hersbach et al., 2020) and wind speed (NCEP/NCAR reanalysis; Kalnay et al., 1996) are existing GLoRS time-series inputs spanning the full 1984–2023 study period, as is reservoir inflow. Atmospheric-river (AR) frequency, intensity, and associated extreme precipitation were derived from the PIKART global atmospheric-river detection and tracking catalog (Vallejo-Bernal et al., 2025), also covering 1984–2023, aggregated annually per reservoir catchment as three separate variables: AR days (the annual count of calendar

days with AR presence in the catchment), AR intensity (the mean total integrated vapor transport, IVT, during AR-active days), and AR extreme precipitation (the annual maximum, across the catchment, of the local 90th-percentile extreme-precipitation threshold on AR-active days — a measure of how extreme the wettest AR-driven conditions were that year). Wildfire burned-area fraction was derived from the MODIS MCD64A1 monthly burned-area product (500 m resolution; Giglio et al., 2021), aggregated to annual burned fraction per catchment; unlike the other drivers, MODIS-derived burned-area data are only available from 2000 onward, so the wildfire driver is evaluated over a shorter (2000–2023) window than the other candidate drivers for reservoirs with records extending before 2000. Reservoir outflow and surface area (a proxy for pool level) are existing GLoRS time-series inputs used as the two retention (reservoir-operations) drivers.

12.5.2. Test 1: Dominant Delivery Driver

What we tested: for each reservoir, which of the seven candidate natural drivers, across four mechanism categories, best explains its sedimentation-rate anomaly. For each driver, we computed the autocorrelation-corrected Pearson correlation between the driver's own annual anomaly and the reservoir's sedimentation-rate anomaly at two lags — the same year (lag 0), and the driver leading sedimentation by one year (lag 1, to capture delayed mobilization, e.g. an antecedent wet year or the prior year's burn scar) — retaining whichever lag gave the larger-magnitude correlation. Because delivery-category variables differ in number (one for hydrologic transport, up to three for atmospheric extremes), we applied a per-category Šidák correction (Šidák, 1967) so categories with more candidate variables are not favored merely by having more chances to show a large correlation by chance.

Results: hydrologic transport (inflow) was the single most common dominant category (196 reservoirs; 91 individually statistically significant after Benjamini-Hochberg FDR correction; Benjamini et al., 2006), followed by hydroclimatic forcing (precipitation and wind speed; 122 reservoirs, 50 significant) and landscape disturbance (wildfire burned-area fraction; 92 reservoirs, 17 significant), with atmospheric extremes (AR days, AR intensity, AR extreme precipitation) dominant least often (89 reservoirs, 14 significant) (Table 12.5). A lag-1 (rather than same-year) relationship was strongest for over a third of reservoirs, underscoring the value of testing delayed as well as contemporaneous mobilization.

Interpretation: a physically interpretable natural driver can be identified for a substantial share of large reservoirs, with inflow variability the most common single pathway, though most individual reservoirs do not reach statistical significance on their own. This is consistent with a genuine but heterogeneous, reservoir-specific mechanistic signal rather than one dominant global pathway.

12.5.3. Test 2: Rate of Significant Driver by ENSO-Response Group

What we tested: because different reservoirs and regions can each have their own significant driver without any one category being globally over-represented in a particular group, we separately tested whether the rate of having any statistically significant dominant driver (the same FDR-corrected significance flag from Test 1, regardless of which category won) differs across the three ENSO-response groups (El Niño-dominated, La Niña-dominated, no clear ENSO signal). Reservoirs were cross-tabulated by ENSO-response group and significant/not-significant status into a 2×3 contingency table, tested via a chi-square test of independence (Pearson, 1900).

Results: 36.8% of El Niño-dominated, 32.1% of La Niña-dominated, and 34.7% of non-responsive reservoirs had a statistically significant dominant driver — an essentially flat rate across groups (chi-square = 0.48, degrees of freedom = 2, $p = 0.79$; Cramér's $V = 0.03$, a near-zero effect size indicating no meaningful association between ENSO-response group and driver significance; Cramér, 1946) (Table 12.6).

Interpretation: reservoirs are no more likely to have an identifiable, statistically significant natural driver simply because they are ENSO-sensitive. Non-ENSO reservoirs have a dominant driver just as often as El Niño- or La Niña-dominated ones. In other words, the mechanistic-driver attribution in Test 1 is not concentrated in, or driven by, the ENSO-classified subset; it reflects a separate source of physical information about each reservoir's catchment rather than re-detecting ENSO sensitivity through another route. This is a useful, if modest, robustness check: it means the mechanistic-driver framework (this section) and the ENSO classification (Section 12.4) are measuring genuinely independent properties of each reservoir rather than one being a redundant restatement of the other.

12.5.4. Test 3: Mechanistic (Delivery) vs. Retention Paired Comparison

What we tested: for each reservoir, whether its best-explaining reservoir-operations (retention) driver — the larger of $|r|$ for outflow or pool level, each tested at lag 0/1 as in Test 1 — explains more sedimentation-rate variability than its best-explaining natural (delivery) driver identified in Test 1, via a paired Wilcoxon signed-rank test (Wilcoxon, 1945) across all reservoirs. Delivery draws from more candidate variables (seven) than retention (two), which structurally favors delivery in a raw effect-size comparison. To account for this, we report two comparisons. The first is a raw comparison (paired test on uncorrected $|r|$). The second, and primary, result applies the same per-category Šidák correction used in Test 1 to each side's best p-value before comparing (paired test on $-\log_{10}$ of the Šidák-adjusted p-value).

Results: retention's raw effect size was larger in most reservoirs (58.7%, $p = 1.3 \times 10^{-5}$) — already statistically significant despite the structural handicap. Correcting for the candidate-count imbalance, retention was the more significant explanatory factor in an even larger share of reservoirs (61.3%, $p = 4.8 \times 10^{-10}$) (Table 12.7).

Interpretation: active reservoir management explains sedimentation-rate variability more often than natural climatic delivery mechanisms at these reservoirs. It is a direct, population-level answer to whether active reservoir operations or natural climate forcing better explains observed variability, and one that argues against attributing sedimentation-rate variability to climate alone. Figure 6.12 maps each reservoir's dominant natural driver category (panel a) and this natural-versus-reservoir-operations comparison (panel b) globally.

Table 12.5 Dominant delivery driver by mechanism category, across all large-scale infrastructure reservoirs.

Mechanism category	N reservoirs (dominant)	% of total	N significant (FDR<0.05)	% significant within category
Hydrologic transport	196	39.3%	91	46.4%
Hydroclimatic forcing	122	24.4%	50	41.0%
Landscape disturbance	92	18.4%	17	18.5%
Atmospheric extremes	89	17.8%	14	15.7%

Table 12.6 Rate of having any statistically significant dominant driver (regardless of which one), by ENSO-response group. The rate does not differ meaningfully across groups, indicating this attribution framework is not itself acting as a proxy for ENSO classification.

ENSO-response group	N significant	N total	% significant
El Niño-dominated	32	87	36.8%
La Niña-dominated	35	109	32.1%
No clear ENSO signal	105	303	34.7%

Table 12.7 Mechanistic (delivery) vs. retention (reservoir-operations) paired comparison, across all large-scale infrastructure reservoirs.

Comparison	N where retention “wins”	%	Test	p-value
Raw (uncorrected r)	293	58.7%	Paired Wilcoxon signed-rank	1.3×10^{-5}
Šidák-corrected (primary result)	306	61.3%	Paired Wilcoxon signed-rank	4.8×10^{-10}