

Integrated analysis of global lakes and reservoirs: Global
reservoirs modeling database, climate-driven changes in thermal
stratification, depth-area-volume relationships, dam operation,
and downstream phosphorus export

by

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Author's Declaration

This thesis consists of material all of which I authored or co-authored: see Statement of Contributions included in the thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

I understand that my thesis may be made electronically available to the public.

Statement of contributions

This thesis consists of a series of co-authored papers. As first author on each paper, I was primarily responsible for the study of designs and execution. The following summarizes the contributions of the co-authors of each paper.

Chapter 2

Philippe Van Cappellen (PVC) and I designed the overall research. I developed the research questions, performed the core data extractions and coding for the Global Reservoir Modeling (GRM) database, and conducted all data analyses and managed the database. Lewis Alcott and Jovana Radosavljevic contributed by refining the manuscript and providing editorial suggestions. Philippe Van Cappellen (PVC) and I wrote the final version of the paper.

Chapter 3

PVC and I designed the overall research. I designed the research questions, performed GRM-based simulation, and data analysis. I wrote the data processing and statistical analysis code and conducted all statistical analyses. I also wrote the initial draft and performed the literature review. PVC and I revised the chapter together.

Chapter 4

PVC and I designed the research. I wrote the code script and developed the Python library, created and managed the GLRDAV database, collected observational datasets, and conducted data visualization and statistical analysis. I also wrote the initial draft and performed the literature review.

Chapter 5

PVC, Chris T. Parsons (CTP), and I designed the research. I organized the model input data and validation data. I ran the hydrodynamic and water quality models, performed the data analysis, and wrote the initial manuscript draft. Yaqian Xu and I worked together to optimize the model and supplementary file of the paper. PVC, CTP, and I finalized the paper. All authors provided feedback on writing the paper.

Abstract

Inland freshwater bodies, including lakes, reservoirs, and wetlands, are critical components of the global freshwater system. They play essential roles in water storage, flow regulation, biodiversity, nutrient cycling, and many other ecosystem services including food production and local climate regulation. However, human interventions such as dam construction, urbanization, intensive agriculture, and climate change significantly alter their hydrological and ecological functions. This underscores the importance of data integration and modeling tools to predictively understand and effectively manage these water bodies to ensure their sustainability and resilience under changing climate and environmental conditions.

With this thesis, I aim to contribute to the comprehensive, global-scale analysis of inland water bodies. I present a new global reservoir water modeling database, abbreviated GRM, that can be coupled with hydrodynamic and water quality simulations. The use of GRM is illustrated by computing temperature changes in nearly 7000 large reservoirs between 1980 and 2019. I also present a database of depth-area-volume (D-A-V) relationships for over 1.4 million lakes and reservoirs worldwide. These relationships provide easy access to essential bathymetric information to users interested in carrying out modeling studies. The D-A-V database is complemented by a Python package that generates bathymetric representations for multidimensional water quality modeling. Lastly, for a reservoir in southern Ontario, I analyze how controlling water level, and the positioning of dam outflow gates can be used to reduce the outflow of total and bioavailable phosphorus, which, more generally, opens the possibility of considering dam operation strategies that help protect downstream water bodies from eutrophication impacts.

Chapter 1 provides an overview of the significance of inland water bodies and the impacts of anthropogenic activities on their biogeochemical dynamics. The chapter reviews existing global databases on lakes and reservoirs, highlighting their strengths and limitations. I further argue that existing global-scale biogeochemical modeling studies of inland waters have primarily relied on simple box models and empirical relationships that lack the ability to capture the complex temporal and multidimensional physical-geochemical-biological interactions in these ecosystems. This gap sets the stage for developing the comprehensive global multidimensional model database presented in Chapter 2.

Chapter 2 describes the development of the Global Reservoir Modeling (GRM) database that integrates multiple existing global datasets to facilitate reservoir hydrodynamic and water quality modeling on a global scale. The current GRM database version brings together 40 years (1980-2019) of diverse data series for nearly 7,000 reservoirs worldwide. The corresponding data are extracted from the following datasets: GRanD for reservoir attributes, ReGeom for bathymetric data, WaterGAP for streamflow, and ERA5 for meteorological parameters. With these data, GRM can generate compatible input files for hydrodynamic and water quality simulations with the popular CE-QUAL-W2 model. Thus, GRM offers researchers a practical and readily usable tool to model changes in reservoir water temperature and mixing regimes and their impacts on water quality, whether for a single or a large selection of the GRanD reservoirs.

Chapter 3 offers an example of the type of global-scale assessments that can be performed with GRM by calculating the temporal trajectories of the thermal gradients in all the reservoirs included in GRM from 1980 to 2019. For each reservoir, a 30×30 depth-length bathymetry is generated by GRM, which is then used in the multithreaded, process-based CE-QUAL-W2 model to calculate the temperature distribution as a function of space and time. The results are illustrated globally by mapping both the surface-to-bottom temperature difference and the distributions of thermocline depth for 1980, 2000, and 2019. The findings confirm not only a widespread increase in surface-to-bottom temperature differences (on average by 0.39 °C per decade) but also a generalized deepening of the thermocline, on average by 1.2 m (around 0.3 m per decade) between 1980 and 2019. The results confirm that global reservoir thermal stratification has both intensified and migrated downward over the past four decades.

Chapter 4 compiles depth–area–volume (D-A-V) relationships for over 1.4 million lakes and reservoirs by merging HydroLAKES and GLOBathy. The resulting GLRDAV database contains > 17 million equations—five polynomial functions (orders 1–5) and one power function for both depth–area and depth–volume—evaluated at 0.1 m depth increments. Validation against ReGeom, GRDL, and in-situ Texas Water Development Board surveys show that 4th- and 5th-order polynomials deliver the highest accuracy. Lower-order polynomials and the power function perform adequately for small, simple basins but not for large waterbodies. A Python package, named “Global Waterbody Calculator”, provides streamlined access to all 17 million equations and coefficients, facilitating rapid bathymetric reconstruction for hydrodynamic and water-quality models. The tool rasterizes shoreline

polygons at 1 arcsecond (~30 m) resolution and rapidly generates full 3-D GeoTIFF bathymetry on a standard desktop, enabling immediate visualization and 3-D model-ready inputs.

Chapter 5 applies the CE-QUAL-W2 model to Fanshawe Reservoir (Ontario, Canada) to test how 33 dam operation scenarios—three dam withdrawal elevations crossed with eleven water-level elevations from 0 to +10 m relative to the current conditions—alter phosphorus retention by the reservoir. Under baseline operation (normal withdrawal, 0 m water level) the reservoir retains only 13% of incoming total phosphorus (TP) annually and can become a net TP and dissolved phosphorus (DRP) source in summer. Switching to surface withdrawal alone boosts the annual TP retention to 20 %, while combining surface withdrawal with a +10 m pool-raise pushes summer retention of TP above 78% and the annual retention to 52%. These gains stem from a four-fold lengthening of the water residence time (peaking at 149 days) and the hydraulic isolation of the P-rich hypolimnion. However, these dam operation and water level conditions also prolong bottom-water hypoxia (with dissolved oxygen < 2 mg/l for around 48 days). The modeling highlights the trade-off between maximizing phosphorus retention and avoiding in-reservoir deoxygenation, underscoring the need for seasonally targeted, adaptive dam management.

Finally, Chapter 6 synthesizes the thesis’s key insights and charts a path forward. It emphasizes how the new global datasets (GRM and GLRDAV) and the Fanshawe case study together advance our understanding of the links between hydrodynamics, nutrient cycling, and dam operation. Looking ahead, this chapter calls for coupling “big-data” archives with process-based and machine-learning models, building reservoir-scale digital twins, and incorporating sediment and groundwater interactions to assess long-term climate and management impacts. Strengthening this predictive framework will be instrumental in safeguarding lakes and reservoirs under accelerating environmental change.

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It has taken many years and many miles, far from my hometown, to finally present this doctoral thesis to you—a piece of work that feels as much like a child as a companion in battle. Nearly three decades of education have been filled with both challenges and joy, with laughter carrying away the difficulties along the way. Life before this feels like a dream within a dream, where my family once gathered around a not-so-big yet boundless round table, and I, filled with excitement, ran outside to light the fireworks my father had bought, eagerly awaiting the chime of midnight.

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Chinese Translation (中文版本更优雅)

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Dedication

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List of Abbreviations

Abbreviations	Definitions
D-A-V	Depth-Area-Volume
GRM	Global Reservoir Modeling
WRT	Water Residence Time
WT	Water Temperature
DO	Dissolved Oxygen
TP	Total Phosphorus
NSERC	Natural Sciences and Engineering Research Council of Canada
GWF	Global Water Futures
GLOBathy	Global Lakes Bathymetry Dataset
GOODD	Global Georeferenced Database of Dams
GeoDAR	Georeferenced Global Dams and Reservoirs Dataset
GLWD	Global Lakes and Wetlands Database
GRanD	Global Reservoir and Dam Database
ReGeom	Reservoir Storage-Area-Depth Dataset
GRDL	Global Reservoir Area-Storage-Depth Data Set
RealSAT	Reservoir and Lake Surface Area Timeseries
GDW	Global Dam Watch
ML	Machine Learning
DL	Deep Learning
GHG	Greenhouse Gas
2-D	Two-Dimensional

3-D	Three-Dimensional
CSV	Comma-Separated value
MD	Maximum Depth
MCMC	Markov Chain Monte Carlo
ΔT	Surface-Bottom Temperature Difference
NUTS	No-U-Turn Sampler
HDI	Highest Density Interval
RMSE	Root Mean Square Error
KDE	Kernel Density Estimation
RCP	Representative Concentration Pathway
GCMs	Global Climate Models
GLRDAV	Global Lakes and Reservoirs Depth–Area–Volume Relationships
MSE	Mean Squared Error
R^2	Coefficient of Determination
PF	Power Function
PRE	Phosphorus Retention Efficiency
P	Phosphorus
N	Nitrogen
DRP	Dissolved Reactive Phosphorus
TRW	Thames River Watershed
ECCC	Environment and Climate Change Canada
UTRCA	Upper Thames River Conservation Authority
ME	Mean Error

MAE	Mean Absolute Error
C-Q	Concentration-Discharge Relationship
WLC	Water Level Control
MOM	Metalimnetic Oxygen Minimum
LLMs	Large Language Models
SD	Standard Deviations

“All models are wrong, but some are useful” - George E. P. Box

Chapter 1

General Introduction

1.1 Overview: global lakes and reservoirs

Lakes and reservoirs are essential components of Earth's hydrological system, playing important roles in water storage, flow regulation, and material cycling (Downing et al., 2006; Messenger et al., 2016; Pi et al., 2022). These freshwater bodies are critical for maintaining biodiversity, supporting fisheries, and providing resources for human activities such as agriculture, power generation, and drinking water supply (Lu et al., 2020; Winton et al., 2019). Globally, over 1.4 million lakes and reservoirs participate in regional water cycles by modulating river flows, sequestering nutrients, and serving as hotspots for ecological activity (Jarvie et al., 2017; Maavara, Chen, et al., 2020; Maavara et al., 2015; Messenger et al., 2016).

However, the widespread development of artificial reservoirs and dams has significantly altered the natural dynamics of river systems (Chen et al., 2023; Grill et al., 2019; Pi et al., 2022; Van Cappellen & Maavara, 2016). The construction of reservoirs, driven by the growing demand for water, energy, and flood control, has led to significant changes in water quality, sediment transport, and biogeochemical cycles (Maavara, Chen, et al., 2020; Winton et al., 2019). Anthropogenic drivers, such as urbanization, agriculture, and climate change further exacerbate these changes, resulting in the disruption of both ecological processes and ecosystem health (Jansen et al., 2024; Maberly et al., 2020; Woolway et al., 2020; Woolway, Sharma, et al., 2021). As a result, understanding the broader global impacts of artificial reservoirs and dams is important for sustainable water management and for addressing the challenges posed by a rapidly changing planetary environment.

1.1.1 Ecological and biogeochemical functions of lakes and reservoirs

Lakes and reservoirs play multifaceted roles within the global hydrological system: they are actively involved in regulating hydrological processes, mitigating extreme events, and supporting ecological diversity (Maavara, Chen, et al., 2020; Woolway et al., 2020). These functions are essential for sustaining both human populations and natural ecosystems, particularly in the face of variable climatic conditions and land use changes (Grant et al., 2021; Maberly et al., 2020; Woolway, 2023).

Global lakes and reservoirs cover a combined surface area of approximately 2.67×10^6 km², accounting for 1.8% of the planet's land area. They span a total shoreline length of about 7.2×10^6

km—nearly four times longer than the world’s ocean coastline—and contain an estimated volume of $1.82 \times 10^5 \text{ km}^3$, which represents 0.8% of global non-frozen terrestrial water reserves (Messenger et al., 2016). These water bodies moderate seasonal and inter-annual variations of water flows (Lu et al., 2020; Winton et al., 2019). Reservoirs, in particular, are engineered to capture excess runoff during high precipitation events, reducing downstream flood risks, while releasing stored water during dry periods to support river flow and water supply needs. This dual role of reservoirs—mitigating floods and providing a steady water source—positions them as essential for water resource stability and environmental flow maintenance (Maavara, Chen, et al., 2020; Zarfl et al., 2015). Additionally, reservoirs support hydroelectric power generation and act as both sources and sinks for various pollutants, significantly influencing downstream water quality (Kao et al., 2022; Y. Xu et al., 2024; Yu, 2020). The global distribution of reservoirs and dams, and their total capacity are illustrated in Figure 1.1.

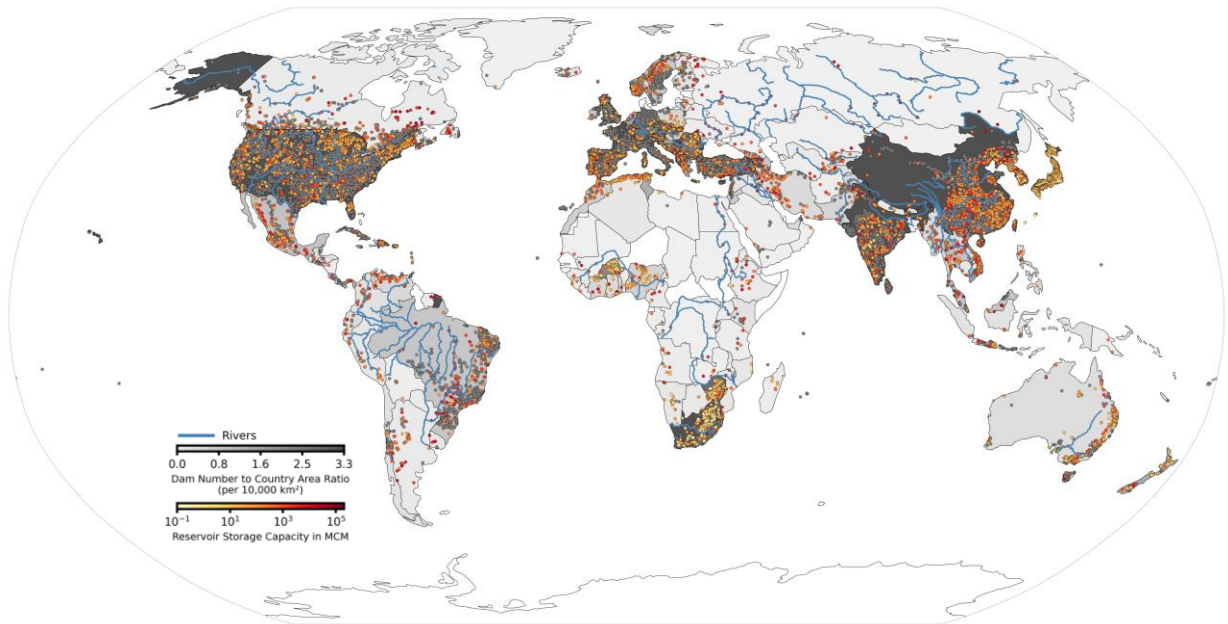


Figure 1.1. Global distribution of dammed reservoirs with storage capacity and dam density per country. Dam and reservoirs data are from GeoDAR (J. Wang et al., 2022), major rivers data from World Bank Group, and country data from Natural Earth.

Lakes and reservoirs also play critical roles in sediment and nutrient retention. Acting as natural traps, they prevent sediments and nutrients such as phosphorus (P) and silicon (Si) from being transported downstream, thereby influencing water quality and sediment dynamics (Jarvie et al., 2012; Maavara

et al., 2015). In natural lakes, nutrient retention and release can lead to chronic impacts on water quality, as nutrients introduced by human activities may accumulate and be gradually released over extended periods, from years to several decades (Jarvie et al., 2012; Sharpley et al., 2013), depending on hydrodynamic conditions and sediment characteristics. (B. Bai et al., 2025) This slow, sustained release, often spanning more than several decades, can create persistent nutrient loading in downstream ecosystems, impacting water quality and productivity in the long term (Jarvie et al., 2013; Sharpley et al., 2013; Van Meter et al., 2018; Xu et al., 2021).

In contrast, artificial reservoirs, which disrupt natural river flow, introduce additional complexity in nutrient dynamics. By altering river connectivity, reservoirs alter nutrient and pollutant retention and release patterns upstream and downstream, influenced by seasonal and operational changes (Grill et al., 2019; Maavara, Chen, et al., 2020; Van Cappellen & Maavara, 2016). For example, under anoxic (oxygen-depleted) conditions that can develop in the hypolimnion of stratified reservoirs, P bound in sediments may be released back into the water column, leading to periodic spikes in bioavailable P concentrations that can fuel algal blooms and degrade water quality (Carpenter, 2008; Orihel et al., 2017; Schindler et al., 2016). This internal phosphorus loading, strongly affected by controlled water level fluctuations, adds to the downstream impacts when P-rich hypolimnetic waters are discharged (Kao et al., 2022; Winton et al., 2019; Z. Xu et al., 2020).

1.1.2 Thermal stratification in lakes and reservoirs

Thermal stratification, an important hydrodynamic phenomenon in lakes and reservoirs, profoundly influences ecological processes by creating distinct temperature layers within the water column, typically warm upper layer (epilimnion), a middle layer with a sharp thermal gradient (metalimnion), and a cooler bottom layer (hypolimnion) (Boehrer & Schultze, 2008; Winton et al., 2019; Woolway et al., 2020; Woolway, Sharma, et al., 2021). Thermal stratification regulates nutrient cycling, as dissolved nutrient species often accumulate in the hypolimnion and are redistributed to surface waters during seasonal mixing events, such as spring and autumn turnover (Winton et al., 2019; Yu, 2020). Stratification also regulates dissolved oxygen distribution patterns, with deeper layers often becoming oxygen-depleted, which in turn regulates the types of organisms and chemical speciation that occur at various depths (Boehrer & Schultze, 2008; Lindenschmidt et al., 2019; Shi et al., 2024; Z. Zhang et al., 2023). Understanding these stratified patterns is essential for predicting nutrient dynamics, primary productivity, and overall ecosystem health in both lakes and reservoirs.

The mixing regimes of lakes (Figure 1.2) are classified according to their thermal stratification characteristics (Woolway et al., 2020):

- Polymictic lakes experience frequent mixing, either continuously or periodically, often due to their shallow depth. These lakes can further be categorized as cold polymictic lakes, which are ice-covered in winter, or warm polymictic lakes, which remain ice-free.
- Dimictic lakes undergo two mixing periods each year, one following summer stratification and one following inverse winter stratification.
- Monomictic lakes experience a single mixing event annually, typically in winter. Cold monomictic lakes develop ice cover in winter, while warm monomictic lakes do not.
- Oligomictic lakes generally remain stratified although they may occasionally undergo complete mixing, for example during a severe storm event.
- Meromictic lakes maintain persistent stratification, often due to their deep bathymetry or the accumulation of a saline hypolimnion.

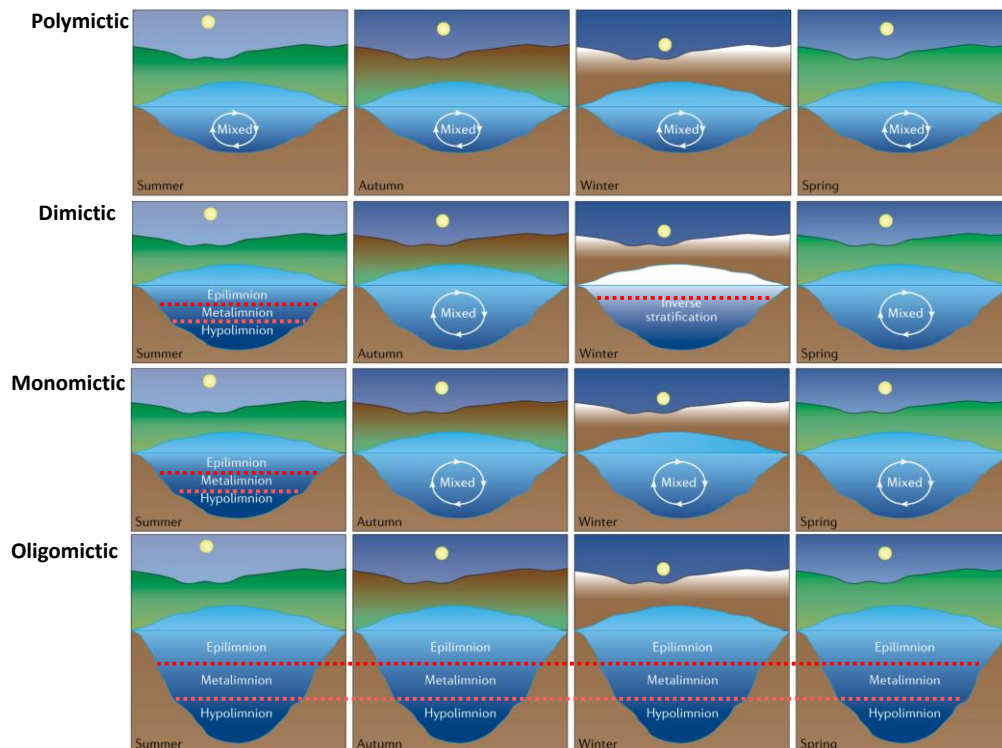


Figure 1.2. Lake and reservoir mixing types, adapted from Woolway et al. (2020).

Thermal stratification in reservoirs can differ from natural lakes due to controlled water level manipulations to control water storage and release (Carr et al., 2020; Lindenschmidt et al., 2019; Morales-Marin et al., 2021). These anthropogenic factors alter the natural water column density layering, impacting oxygen and nutrient distributions throughout the year and shaping the reservoir's ecological environment (Mi et al., 2020; Shi et al., 2024; H. Wang et al., 2024; Y. Xu et al., 2024; Yigzaw et al., 2019).

From an ecological perspective, stratified habitats in both lakes and reservoirs support diverse aquatic life, ranging from microorganisms to fish and birds, thus contributing to biodiversity and ecosystem functionality (Chen et al., 2023; Jones, 2006). The physical characteristics of these water bodies, including depth, surface area, and thermal stratification, influence species distribution and productivity, as well as the availability of essential nutrient elements, such as P, N, and Si (Elçi, 2008; Kirillin & Shatwell, 2016; Zhao et al., 2021). The occurrence and intensity of thermal stratification in both lakes and reservoirs are thus key to ecosystem health and productivity.

1.2 Existing global climate, water quality, and hydrological databases

1.2.1 Global databases for lakes and reservoirs

Various global databases provide valuable information on lakes and reservoirs that enable researchers to analyze and model these water bodies (Table 1.1). Here, I present an overview of existing large-scale lake and reservoir databases worldwide, updated as of January 2025. These existing databases provide critical information about lakes, dams, and reservoirs, including location, average flow rates, dam specifications, and polygon boundaries. However, they report less frequently depth-area-volume (D-A-V) relationships of water bodies. For instance, the most extensive database, HydroLAKES, covers 1,427,688 water bodies globally and provides primary information such as location, surface area, and volume. However, D-A-V relationships are lacking despite being crucial for accurately modeling water storage changes and stratification or for use in process-based water quality models that depend critically on the bathymetry (Messenger et al., 2016). By contrast, GLOBathy includes approximations of D-A-V relationships, which are generated using an empirical power function based on the estimated depths (Khazaei et al., 2022). ReGeom, and GRDL further employ different methods to provide D-A-V relationships at different resolutions (Hao et al., 2024; Yigzaw et al., 2018). More recently, GWD was introduced as a new database that considers all major constructed flow barriers (including dams, weirs, barrages, locks, reservoirs, and impoundments, regulated ponds), hence

delivering the most up-to-date information on human-built structures that alter global river flow patterns (Lehner et al., 2024).

Table 1.1. Summary and limitations of global lakes and reservoirs databases.

Database (reference)	Number of waterbodies/barriers/dams	Data types	Limitations
GLOBathy (Khazaei et al., 2022)	1,427,688	Name, location, estimated depth, D-A-V	Wrong units in D-A-V file, oversimplified depths and D-A-V equations, not applicable for water level fluctuations or user modifications
HydroLAKES (Messenger et al., 2016)	1,427,688	Name, location, volume, surface area, discharge	Only basic information, no D-A-V relationships
GOODD (Mulligan et al., 2020)	25,931	Location, catchment area	Only limited locations and dam watershed information
GeoDAR (Wang et al., 2022)	22,560	Name, location, dam information	Mainly provides location, no D-A-V relationships or other detailed information
GLWD (Lehner & Döll, 2004)	253,067	Wetlands and lakes: name, location	Focuses mainly on wetlands
GRanD (Lehner et al., 2011)	6,824 (V1.0) 7,320 (V1.3)	Name, location, dam information, discharge	Only limited (major) dams and reservoirs, no D-A-V relationships
ReGeom (Yigzaw et al., 2018)	6,824	Name, location, D-A-V	Oversimplified shapes of waterbodies; data errors Data require high GPU resources for extended training, heavily dependent on the precision of the original images, not user-friendly
GRDL (Hao et al., 2024)	7,250	Name, location, D-A-V	Not user-friendly, lacks bathymetry data and detailed information.
RealSAT (Khandelwal et al., 2022)	681,137	Surface area (lakes and reservoirs)	No D-A-V relationships, limiting applicability for process-based water quality modeling
GDW (Lehner et al., 2024)	41,145	Name, location, type, barrier and dam information	
GLRSED (B. Bai et al., 2025)	2,171,143	Name, location, surface area	Only surface area

1.2.2 Limitations and gaps of current fresh water body datasets

While databases like HydroLAKES, GLOBathy, ReGeom, and GRDL offer extensive spatial coverage and, in some cases, D-A-V relationships, they largely function as stand-alone resources and are not easily integrated with hydrodynamic and water quality modeling tools (Hao et al., 2024; Khazaei et al., 2022; Messenger et al., 2016; Yigzaw et al., 2018). Specifically, these databases lack flexible D-A-V relationships describing bathymetry, as well as the ability to seamlessly link to meteorological and hydrological datasets, making time-sensitive updates and adjustments difficult (Neumann et al., 2021; Tiyyasha et al., 2020; Tsai et al., 2021). These limitations hamper their utility for modeling water quality, contaminant transport, and ecological processes in lakes and reservoirs across varied geographic and climatic conditions.

For researchers focusing on local studies, the direct use of global databases is often hampered by coarse spatial resolution and incompatible data formats. Yet, in cases where acquiring complete data sets across one or several water bodies is prohibitive or impractical, global databases can still play an important role in regional estimations and upscaling studies. Thus, there is a need for approaches that enable the downscaling of the information and data from global databases for local applications, for example by extracting bathymetric representations that can serve as input for hydrological and water quality modeling. Such approaches would increase the interoperability across databases and with modeling platforms, hence, increasing the accessibility and use of the existing global databases.

1.3 On the importance of global scale modeling of lakes and reservoirs

1.3.1 Current research in local to global hydrosystem modeling

Hydrodynamic and water quality models are essential tools for advancing our predictive understanding of lake and reservoir functioning. They provide insights into water flow dynamics, thermal stratification, and nutrient cycling. Various models, including AQUATOX, CE-QUAL-W2, EFDC, MIKE, SWAT, and WASP (Table 1.2), offer different features and strengths in surface water quality modeling (J. Bai et al., 2022; Burigato Costa et al., 2019; Costa et al., 2021). These detailed models, however, are rarely used to comparatively analyze water quality responses of large numbers of lakes and reservoirs across diverse climatic regions. Such global-scale analyses continue to rely on highly simplified models, for example one-reservoir (box) and one-dimensional models. These models do not account for the complex time-dependent hydrodynamics of lakes and reservoirs

(Maavara et al., 2015; Woolway & Merchant, 2019; Maavara, Chen, et al., 2020) and, hence, are limited in their ability to account for the role of bathymetry and hydrological processes. Consequently, they are not suitable to reproduce the observed spatial and temporal heterogeneity of, among others, nutrient distributions and temperature profiles (Jansen et al., 2024; Lindenschmidt et al., 2019; Lu et al., 2020; Morales-Marin et al., 2021; Soued et al., 2022). It is legitimate to question to what degree simplistic physical representations of lakes and reservoirs cause biases when assessing water quality and ecological health, especially under changing climate scenarios.

Table 1.2. Review of major surface water quality model.

Model name	Characteristics	Abilities and advantages	Main limitations
AQUATOX (Park et al., 2008)	1-D	Open source, sensitivity and uncertainty analysis tools	Does not fully include stratification, metal and algal dynamics
CE-QUAL-W2 (Cole & Wells, 2017)	2-D laterally averaged hydrodynamic and water quality model	Open source, includes sediment module, and flexible water quality parameters.	Does not capture lateral variations
EFDC (J. Bai et al., 2022; Costa et al., 2021)	1-D/2-D/3-D surface water modeling system	Multiple dimensionalities, commercially maintained (EFDC+)	Only open source for EFDC (old version), limited ecological modeling
MIKE (J. Bai et al., 2022)	1-D/2-D/3-D surface, groundwater and flood water modeling system	Includes calibration tools and dam break scenarios	Not open source and limited ecological modeling
SWAT (Costa et al., 2021)	River basin scale model for watersheds and land management	Open source, simulates nonpoint pollution and handles large river basins	Not suited for individual reservoirs and lakes
WASP (Wool et al., 2020)	1-D/2-D/3-D aquatic model systems	Open source, uncertainty analysis tools, comprehensive modules	Need to use external linkage of hydrodynamic module

Another key limitation is the lack of integration between global databases and process-based models. While machine learning (ML) and deep learning (DL) models are increasingly employed for their capacity to handle large, heterogeneous datasets, they often lack the mechanistic underpinnings needed to predict process dynamics accurately (D. Feng et al., 2022; Lian et al., 2023; Tiyasha et al., 2020). Conversely, process-based models provide detailed representations of physical and chemical processes but face computational inefficiencies and challenges in incorporating real-time data when considering large spatial and temporal scales (Neumann et al., 2021; Reichstein et al., 2019; Xu et al.,

2024). This separation between model types limits their respective scope, particularly in global simulations where combined approaches would allow one to capture both the empirical patterns and mechanistic drivers of hydrological and ecological processes. While physical process models have been integrated with data-driven models, the same integration of biogeochemical process models has remained limited (Kim et al., 2021; H. Li et al., 2024; Lian et al., 2023; Mohammed et al., 2022; Neumann et al., 2021; Tsai et al., 2021; C. Xu et al., 2024). This gap highlights the need for further efforts to enhance the integration of biogeochemical modeling with databases and data-driven methodologies to improve the predictive understanding of complex ecological and nutrient cycling processes and their responses to changing anthropogenic pressures.

Data availability further complicates these challenges. Many regional to global scale modeling studies of the hydrological and biogeochemical roles of lakes and reservoirs rely on historical datasets that may no longer be able to capture contemporary ecosystem dynamics (Korver et al., 2024; Meyer et al., 2020; Woolway et al., 2020; Yao et al., 2023, 2024). Consequently, large-scale models usually lack proper validation of their predictive power within local contexts. Addressing all of the above limitations calls for a shift toward more efficient hybrid frameworks that blend data-driven and mechanistic modeling and can deliver accurate, scalable predictions at the global scale.

1.3.2 The need for comprehensive global water quality models for waterbodies

Given the limitations in the coupled use of current global databases and water quality modeling frameworks, there is a need for a new generation of comprehensive, global models or modeling databases that integrate data-driven and process-based approaches. Such models should leverage advances in remote sensing, in situ sampling, historical data reconstruction, and ML/DL methodologies to enable high-resolution simulations of lake and reservoir water quality at large spatial and temporal scales. These integrated models must bridge the current gap between distributed empirical data and mechanistic process representations, allowing for simulations of thermal stratification, nutrient cycling, and water quality responses under diverse and changing environmental conditions.

Importantly, these new modeling tools must be adaptable to different topographical and climatic contexts of lakes and reservoirs, allowing researchers to evaluate ecosystem responses across regions and pressures, for example, by capturing the impacts on water quality of climate warming and changing nutrient inputs along the temperate to tropical climate gradient. Such predictions should

build on the general understanding and modeling capabilities for thermal stratification, nutrient transport, and sediment interactions, irrespective of the climate zone. More integrated modeling approaches would enable the simulation of potential management scenarios, evaluate the impacts of policy decisions, and guide adaptive strategies to mitigate changing environmental risks. The creation of global, multidimensional lake and reservoir modeling tools thus represents not only a scientific challenge but a practical necessity for ensuring the future health of these critical ecosystems.

1.4 Research questions and thesis structure

My thesis is organized to systematically address the complexities of lakes and reservoirs modeling application frameworks at global scales. The emphasis will be on developing D-A-V relationships for global lakes and reservoirs and their importance in supporting analyses of thermal regimes, nutrient cycling, and reservoir management in the context of water quality protection.

Specifically, I aim to address the following research questions:

- 1. How can large datasets, comprising satellite remote sensing data, reanalysis data, and historical records, be integrated to assemble a general modeling framework for reservoirs?**
- 2. What are the global-scale effects of climate warming on the thermal stratification of reservoirs?**
- 3. How can D-A-V relationships be generalized and applied globally to facilitate high-resolution simulations of the hydrodynamics of lakes and reservoirs?**
- 4. What adaptive water level and outflow management strategies can optimize the mitigation of excess phosphorus export from reservoirs, in the context eutrophication control?**

I begin the research portion of this thesis (Chapters 2–5) by developing the Global Reservoir Modeling (GRM) database, which provides the modeling framework backbone for Research Question 1 and underpins the subsequent analyses of climate-driven stratification (Research Question 2), global lakes and reservoirs bathymetric generalization (Research Question 3) and reservoir’s adaptive management scenarios (Research Question 4).

Chapter 2 presents the construction of the Global Reservoir Modeling (GRM) database, designed to consolidate datasets from global databases and standardize inputs for use in hydrological water quality models. GRM incorporates a 40-year data time series and serves as a foundational resource for large-scale simulations of reservoirs.

Chapter 3 uses the GRM to investigate the response of the thermal stratification of reservoirs to ongoing climate warming. Specifically, it simulates how the surface–bottom temperature difference—and hence the overall thermal gradient—evolved from 1980 to 2019 under global air-temperature trends.

Chapter 4 introduces a new D-A-V modeling tool applicable to over 1.4 million freshwater bodies globally. Users can choose polynomial or power-law forms via an open-source Python package, which also renders 3-D bathymetric visualizations.

Chapter 5 focuses on a case study, Fanshawe Reservoir, Ontario. I use the CE-QUAL-W2 model to investigate 33 scenarios of water level control and their impacts on the reservoir thermal and chemical dynamics. The results imply that, in principle, the operation of the Fanshawe Dam could be optimized to reduce the downstream export of the limiting nutrient phosphorus.

Chapter 6 synthesizes the findings of the thesis and discusses future directions in global lakes and reservoir water quality modeling. I emphasize the potential of combining big data with process-based models to address current model limitations and more comprehensively address climate and land use change impacts on freshwater resources.

Chapter 2

**Global Reservoir Modeling (GRM) database: A user-oriented tool
for integrating global datasets into reservoir water quality modeling**

2.1 Summary

Continued population growth is increasing demands for water and energy. As a result, the world continues to experience a surge in global dam construction. Dams and reservoirs have consequently become interdisciplinary research hotspots to determine their impact on, for example, flow regimes and biodiversity of river systems, nutrient fate and transport, and greenhouse gas emissions. Existing global databases provide key information on dam and reservoir attributes, as well as climate conditions and river flows. To facilitate the use of these global databases in process-based water quality modeling of reservoirs, we present the Global Reservoir Modeling (GRM) database, which integrates data from the Global Reservoir and Dam (GRanD), Reservoir Storage-Area-Depth (ReGeom), WaterGAP v2.2d, FutureStreams, and ERA5 reanalysis databases. Through GRM, users can download multi-decadal water discharge, water temperature, and meteorological data (from 1980 to 2019) in compatible output file formats. In addition, GRM generates simplified reservoir bathymetries based on the user-defined number of depth segments. The GRM output files can directly be entered as input to the well-known water quality model CE-QUAL-W2. As such, GRM bridges the gap between existing global reservoir datasets and multidimensional water quality modeling applications.

2.2 Introduction

Population growth has driven agricultural intensification, economic expansion, and rising energy demand. One of the strategies employed to support these developments has been the construction of dams for flood control, irrigation, water supply, and hydropower generation (Lehner et al., 2024; J. Wang et al., 2022; Zarfl et al., 2015). The ramifications of dam construction extend beyond structural implications, imparting both biogeochemical and ecological shifts, both within and downstream of reservoirs (Maavara, Chen, et al., 2020; Winton et al., 2019). An example is that the accelerated phosphorus remobilization under stratification can lead to eutrophication (Maavara, Akbarzadeh, et al., 2020; Powers et al., 2016; Sun et al., 2022; Van Meter et al., 2018; Wu et al., 2023). River damming can also inflict disruptions on fisheries and aquaculture (Nobile et al., 2020; Song et al., 2019; Wang et al., 2015). Beyond local impacts, the carbon dioxide and other greenhouse gas (GHG) emissions from reservoirs are raising concerns about climate warming (Battin et al., 2023; Harrison et al., 2021; Maavara, Chen, et al., 2020; Soued et al., 2022).

The global biogeochemical and environmental effects of dam construction and dammed reservoirs represent an active area of research (Maavara, 2017; Maavara, Chen, et al., 2020; Maavara et al., 2015, 2017; Van Cappellen & Maavara, 2016). Especially, how these effects evolve over the entire life cycle of a dam remains incompletely characterized (Lu et al., 2020; Maavara, Akbarzadeh, et al., 2020; Maavara, Chen, et al., 2020; Maavara et al., 2015, 2014). The impacts of a dam reservoir on the river system can be positive or negative, depending on regional ecological management goals. For example, some reservoirs may be nutrient and pollutant sinks, thereby reducing the corresponding loading to the downstream reaches of the river and receiving water bodies. Alternatively, other reservoirs may behave as a source of certain pollutants, for instance because of remobilization from bottom sediments (i.e., internal loading) (Orihel et al., 2017; Powers et al., 2016; Sharpley et al., 2013; Yu, 2020). As a result, the water quality management potential of reservoirs has become an interdisciplinary scientific hotspot (Jarvie et al., 2012, 2013; Powers et al., 2016; Shi et al., 2024; Y. Xu et al., 2024). Various datasets have been assembled that provide detailed information on reservoirs and dams, including data on water discharge, water temperature, and climate conditions. Nonetheless, there remains a large gap between these databases and their utilization for water quality model applications. Incompatible model algorithms, data formats, and input/output files make it difficult to efficiently transfer the contents of large global databases to environmental models.

While previous studies have focused on simulating the coupled hydrodynamics and water quality of individual dammed reservoirs using diverse modeling tools, the systematic investigation of the global biogeochemical importance of dammed reservoirs has only recently begun (Maavara, Chen, et al., 2020; Shi et al., 2024; J. Wang et al., 2022; Z. Wang et al., 2024; Winton et al., 2019). However, the lack of user-friendly tools to generate input data for advanced reservoir models across large temporal and spatial scales continues to pose a significant challenge. Currently, there is no integrated database for global dammed reservoirs that can support two-dimensional (2D) and three-dimensional (3D) hydrodynamic and water quality modeling applications.

To bridge the gap between conventional datasets and reservoir management research, and to facilitate the exploration of the impact of dammed reservoirs on biogeochemical cycles and water quality globally, we present the 2D/3D Global Reservoir Modeling database (GRM). GRM includes the 6,824 major dams and reservoirs reported in the Global Reservoir and Dam database (GRanD). Users can directly add location information (latitude and longitude) and parameters, such as the wind coefficients, into the GRM batch control file, and access model-ready bathymetry files, water

discharge and temperature files, and meteorological data files. All this information is in the right format for use by the CE-QUAL-W2 water quality model. GRM is a new, user-friendly and comprehensive reservoir modeling database that supports research and management strategies to protect water quality and ecosystem health of reservoirs and downstream receiving water bodies.

2.3 Methods and data sources

This section describes the data integration processes and algorithm development of GRM. The first subsection, “GRM workflow”, identifies the databases and data sources drawn upon by GRM (Figure 2.1). The second subsection, “GRM data integration”, outlines the basis for computing simplified bathymetries of the reservoirs and generate location-specific data files on discharge, climate and computation grids. Next, a brief review of the CE-QUAL-W2 water quality model is provided, followed by an example of a global application of GRM coupled to CE-QUAL-W2. Additionally, to accelerate large-scale reservoir modeling, we offer a multithreading Python script to run multiple reservoir simulations concurrently (e.g., GRM_run_public.py). All GRM versions and simulation scripts have been uploaded in the Federated Research Data Repository (FRDR) <https://doi.org/10.20383/103.0792>.

2.3.1 GRM methodological framework and development

GRM draws from five pre-existing global databases: ReGeom (Yigzaw et al., 2018), Global Reservoir and Dam database (GRanD) (Lehner et al., 2011), WaterGap v2.2d (Müller Schmied et al., 2021), FutureStreams (Bosmans et al., 2022), and the ERA5 (Hersbach et al., 2020) reanalysis database. To integrate these datasets, the latitude and longitude of the 6,824 GRanD reservoirs were matched with the spatial grids of the global netCDF files, and their time series were standardized to cover the period 1980 to 2019. Monthly water discharge data were extracted from WaterGap v2.2d, weekly reservoir inflow water temperatures from FutureStreams, and daily meteorological data (air temperature, wind vectors, and cloud cover) from ERA5. The processed data for each reservoir were saved as time series comma-separated values (CSV) files for use in subsequent process-based modeling (Figure 2.1).

The GRM workflow consists of three main stages:

(1) Dataset integration: Pre-existing databases are ingested into GRM, where spatial matching aligns reservoir coordinates with the grid points of the global datasets. Temporal alignment (1980–2019) standardizes all input data to ensure consistency across datasets.

(2) Data processing: The integrated datasets are processed into reservoir-specific variables, including bathymetric data (ReGeom), inflow and outflow water time series (WaterGap v2.2d), water temperature series (FutureStreams), and meteorological variables (ERA5). This stage also harmonizes data resolutions and formats, preparing them for downstream modeling.

(3) Model execution: GRM modules handle utility functions, and the pre-execution of CE-QUAL-W2 models where model execution is structured into multi-threaded modules using Python's **ThreadPoolExecutor**. Each reservoir simulation is executed as a thread, allowing for parallel processing of multiple reservoir models. Our multi-threaded modules also provide simulation log files. The log file systematically records key aspects of the process, including task initiation and completion, file preparation checks, errors (e.g., missing inputs or runtime anomalies), and reasons for abnormal terminations such as timeouts. These logs facilitate real-time monitoring, post-simulation analysis, and debugging. The results from all threads are compiled and integrated for further analysis, ensuring a scalable and reliable approach to large-scale reservoir modeling. Further details can be found in the “**GRM_run_public.py**” file uploaded in FRDR.

Global Reservoir Model

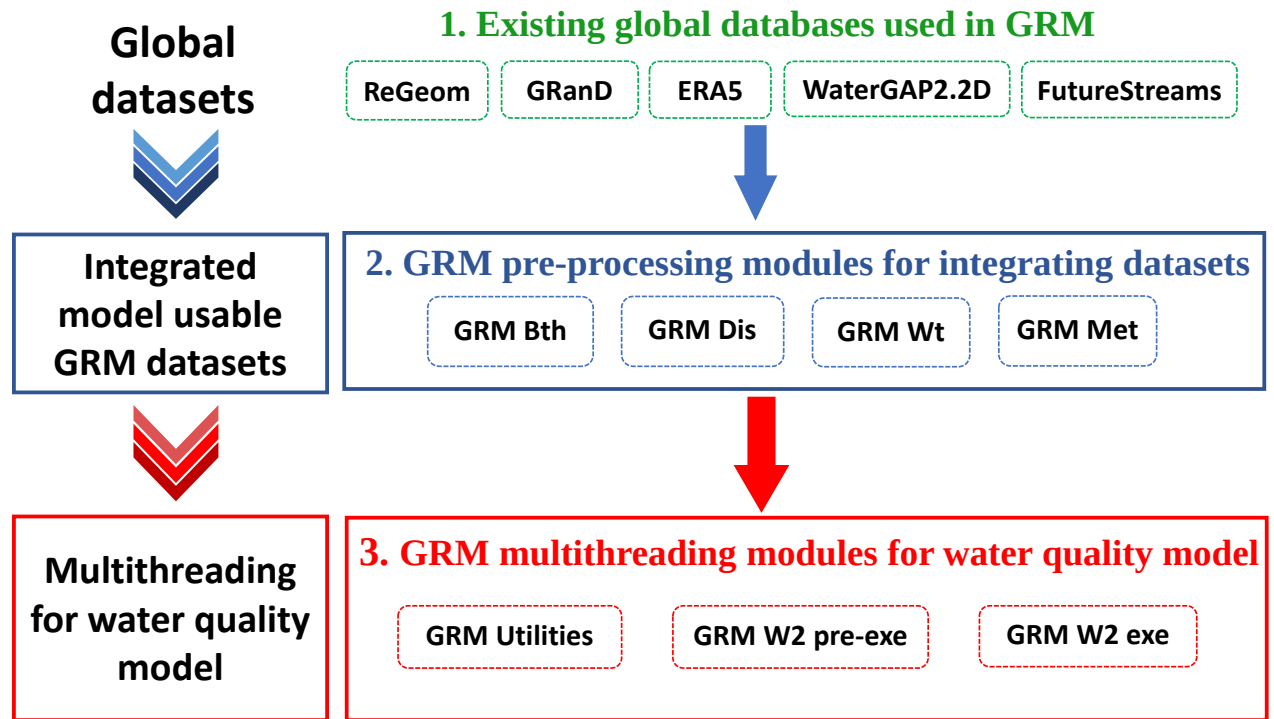


Figure 2.1. Workflow diagram for GRM (GRM components: GRM Bth: Bathymetric data for each reservoir, GRM Dis: Inflow and outflow time series for each reservoir, GRM Wt: Time series inflow water temperature, GRM Met: Meteorological data, including air temperature, dewpoint temperature, wind direction and speed, and total cloud cover. GRM concurrent processing: Multithreading tools for efficient GRM execution, recording simulation details. GRM W2 pre-exe: CE-QUAL-W2 pre-executable files for all reservoirs in GRM. GRM W2 exe: CE-QUAL-W2 executable files used to run all reservoirs in GRM).

2.3.2 GRM development functions

(1) Bathymetry modeling functions:

GRM relies on ReGeom (Yigzaw et al., 2018) to calculate reservoir dimensions and volumes, and on GRanD (Lehner et al., 2011) for reservoir locations and identifications (IDs). Maximum depth of the respective reservoir which relates to 95% of dam height in meters (Yigzaw et al., 2018). Each reservoir is discretized into a default number of vertical layers ($N_z = 30$) and longitudinal segments ($N_x = 30$), producing a 30×30 structured grids. Users may optionally adjust the number of layers and segments depending on the resolution needs and computational constraints of the model application. Higher resolution bathymetry offers improved geometric accuracy but at the cost of increased computational demand.

The bathymetric width of each layer is calculated using a volume-based derivation method, combined with a binary mask structure that controls the effective cross-sectional shape. The equations governing the generation of each layer's geometry are presented below. Finally, we use Python script to convert all grids, ensuring they are compatible with the CE-QUAL-W2 model (Figure 2.2). The calculation process is detailed below, providing data on length, width, and layer height as described in Equation 2-1 to Equation 2-8.

Shape ratio and geometry logic:

GRM defines a shape control parameter $R \in [0, 1]$ to determine the horizontal expansion profile of reservoir cross-sections:

$R = 0$: segments increase linearly $\rightarrow$ triangular shape

$R = 1.0$: segments have uniform length $\rightarrow$ rectangular shape

$0 < R < 1.0$: mix of both $\rightarrow$ trapezoidal shape

$$R \in [0, 1] \quad \text{Equation 2-1}$$

Layer thickness (Δz):

$$\Delta z = \frac{H_{\max}}{N_z} \quad \text{Equation 2-2}$$

Segment length (Δx):

$$\Delta x = \frac{L_{\text{total}}}{N_x} \quad \text{Equation 2-3}$$

Binary mask for reservoir geometry types:

The active area of each 2D cross section is defined by a binary mask $\mathbf{M}_{i,j} \in \{0, 1\}$ where:

$$\mathbf{M}_{i,j} = \begin{cases} 1, & i \leq [\beta \times j] \\ 0, & \text{otherwise} \end{cases}, \quad \beta = \frac{N_z}{N_x} \quad \text{Equation 2-4}$$

This produces a diagonal or trapezoidal truncation in the 2D matrix. To match CE-QUAL-W2's convention (surface layer on top), the mask is vertically flipped before export.

Effective horizontal length of layer i:

$$L_i = \Delta x \sum_{j=1}^{N_x} \mathbf{M}_{i,j} \quad \text{Equation 2-5}$$

Layer volume and layer width:

$$\Delta V_i = V_i - V_{i-1} \quad \text{Equation 2-6}$$

$$W_i = \frac{\Delta V_i}{\Delta z \times L_i} \quad \text{Equation 2-7}$$

Each grid cell width ($b_{i,j}$) is determined by applying the binary mask:

$$b_{i,j} = W_i \times \mathbf{M}_{i,j} \quad \text{Equation 2-8}$$

Where:

- H_{max} : maximum depth (as 95% of dam height)
- L_{total} : total reservoir length
- N_z : number of vertical layers (default = 30)

- N_x : number of longitudinal segments (default = 30)
- i : vertical index (bottom to top)
- j : longitudinal index (upstream to downstream)
- β : defines the maximum vertical extent of active cells for each segment
- ΔV_i : volume change between adjacent layers
- L_i : active horizontal length from the binary mask

GRM outputs bathymetry files in three pre-defined shapes per reservoir:

Output file	Shape type	Shape ratio R
bth_1.csv	Rectangular	1.0
bth_2.csv	Triangular	0.0
bth_3.csv	Trapezoidal	0.5 (default)

Users may also specify any intermediate value of $R \in [0,1]$ to generate custom geometries. The function `write_parsed_data_to_bth_csv` handles formatting and header generation, including required CE-QUAL-W2 formatting. A detailed usage guide and code documentation is available in the GRM repository on FRDR: <https://doi.org/10.20383/103.0792>

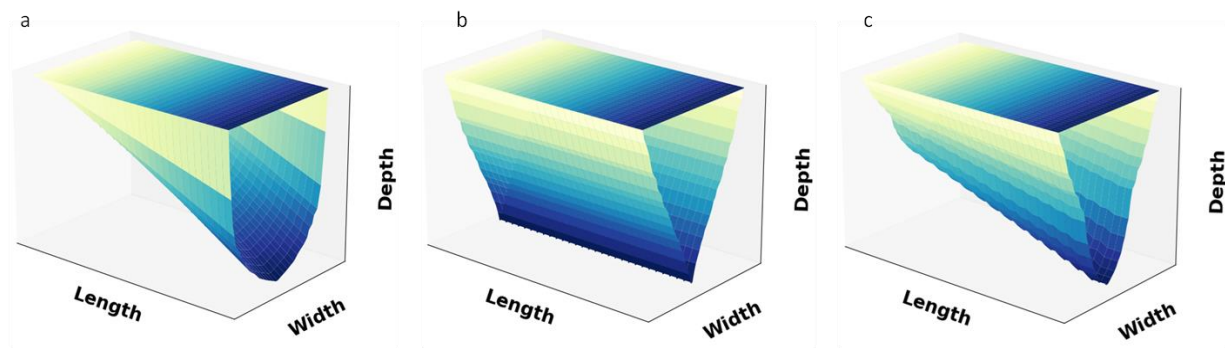


Figure 2.2. Conceptual diagram illustrating the three simplified dam typologies: (a) Triangular; (b) Rectangular; (c) Trapezoidal (longitudinal and vertical dimensions: 30 x 30 grids).

(2) Water discharge and water temperature modeling data and functions:

The integration of the WaterGAP v2.2d (Müller Schmied et al., 2021) database into GRM yields long-term discharge files tailored for individual reservoirs based on their location information. WaterGAP v2.2d includes simulations of global water consumption across sectors such as irrigation, livestock, domestic use, manufacturing, and thermal power generation (Müller Schmied et al., 2021). Similar to the discharge modeling process, the GRanD (Lehner et al., 2011) database's latitude and longitude details are used to accurately associate the temperature data of FutureStreams (Bosmans et al., 2022) with individual reservoirs.

(3) Meteorological data:

ERA5, developed by the European Centre for Medium-Range Weather Forecasts, offers high-resolution climate data at a grid resolution of 0.25° x 0.25° (Hersbach et al., 2020). Within GRM, ERA5 data undergoes processing to extract four-hour global mapping intervals (00:00, 06:00, 12:00, 18:00 UTC). The total climate data size is 1.02TB, and this is further refined to produce daily average climate data, customized for each reservoir location.

Parameters derived from hourly ERA5 data include "2 m air temperature", "2 m dewpoint temperature", and horizontal wind components. For improved usability, GRM converts temperature data from degrees Kelvin to degrees Celsius. The "10 m u component of wind" (u) and "10 m v component of wind" (v) are employed to compute wind speed and direction. Additionally, the total cloud cover data, originally dimensionless in the ERA5 database (ranging from 0 to 1), is transformed into a scale from 0 (clear skies) to 10 (overcast) for utilization in the CE-QUAL-W2 water quality model.

Equations for wind metrics:

$$\text{Wind speed} = \sqrt{u^2 + v^2} \quad \text{Equation 2-9}$$

Wind direction calculation:

$$\text{Angle between vectors} = \arctan \frac{u}{v} \quad \text{Equation 2-10}$$

Windspeed has units of m s^{-1} and all angles between each u and v wind component are transferred to 0 to 2π . To summarize, GRM allows users to access and interpret meteorological data sourced from ERA5, presenting it in a format conducive to modeling with CE-QUAL-W2.

(4) GRM concurrent module for CE-QUAL-W2 modeling

The CE-QUAL-W2 model is a comprehensive, open-source, 2D laterally averaged hydrodynamic and water quality model. It has been used and validated across a wide array of water bodies including reservoirs, lakes, estuaries, rivers, and pit lakes (Cole & Wells, 2017). The model integrates hydrodynamics, water quality, and sediment and requires bathymetry data to develop computational segments. Notably, CE-QUAL-W2 can simulate over 60 variables and more than 70 water quality fluxes (Cole & Wells, 2017), including nutrient concentrations, dissolved oxygen, and user-defined variables.

To bridge the capabilities of the CE-QUAL-W2 model with GRM, a concurrent framework has been developed. The concurrent module of GRM is designed to enable users to modify execution parameters, such as elapsed time, closure time, and the quantity of executable files to run in tandem. Moreover, users can further refine simulations by adjusting input files, such as measured water inflow temperature, measured inflow etc., specific to a reservoir of interest under its designated ID. This integration not only accelerates the simulation workflow but also optimizes the allocation of computational resources, showcasing GRM's dedication to user-centered innovation and its advanced role in the field of water quality modeling.

2.4 Example applications: Global reservoir surface and bottom temperature

To demonstrate GRM's functionality, we present an application that highlights its ability to support simulation of large numbers of global reservoirs. Figure 2.3 illustrates the spatial distribution of global reservoir temperatures, showcasing surface and bottom temperature conditions for the year 1980 versus the year 2019. Simulation results reveal that the global surface water temperature of reservoirs increased an average by 0.47°C per decade from 1980 to 2019, while the bottom water temperature rose an average by 0.10°C per decade under triangular reservoirs' shape. These findings align with previous studies on surface water temperature trends, which reported increases of $+0.34^{\circ}\text{C}$ to $+0.37^{\circ}\text{C}$ per decade (O'Reilly et al., 2015). For bottom water temperature, an analysis of 102 lakes across North America and Europe demonstrated a rise of 0.06°C per decade (Pilla et al., 2020).

Surface temperatures are more susceptible to the effects of climate warming, exhibiting a faster rate

of increase compared to bottom temperatures. These results underline the GRM's capability to capture water temperature variations at varying depths, enabling comprehensive investigations into the impacts of climate change and anthropogenic activities on reservoir thermal structures.

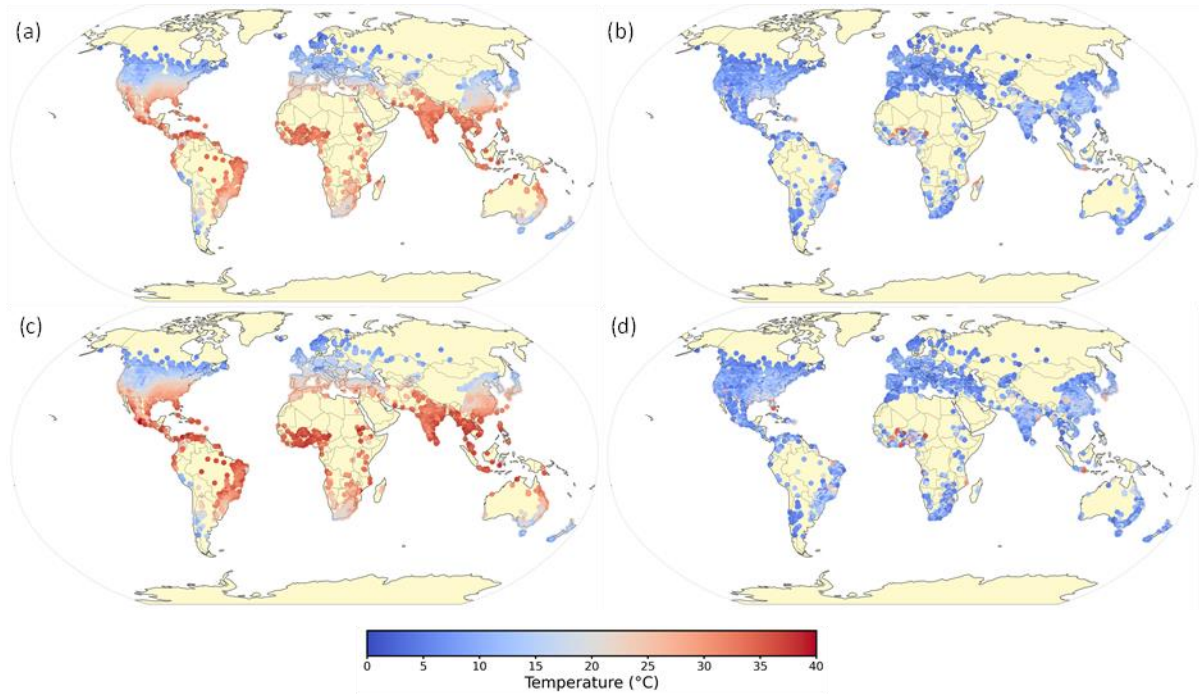


Figure 2.3. Global distribution of surface and bottom layers in 1980 and 2019:(a) Surface temperature in 1980, (b) Bottom temperature in 1980, (c) Surface temperature in 2019, (d) Bottom temperature in 2019 (GRM simulation results).

2.5 Technical validation

The validation of global databases faces significant challenges due to the lack of long-term, globally measured data. However, despite this limitation, the reliability of the GRM model is supported by the integration of multiple well-established datasets, all of which have undergone peer-reviewed validation. Here, we provide bathymetry database validation, and surface water temperature validation

(1) Bathymetry validation:

GRM's bathymetric data is validated by comparing it with existing global databases shown in Figure 2.4. The volume information is derived from the GRanD database (Lehner et al., 2011), which was

validated by Lehner et al., and the ReGeom dataset, which was validated by Yigzaw et al. in 2018. GRM demonstrates strong performance in capturing reservoir topographic characteristics. Figure 2.4 presents the validation of total reservoir volume using triangular and rectangular shapes, with R^2 values of around 0.98, indicating a high degree of correlation between GRM results and previous databases. Additional validations for trapezoidal reservoir shapes are provided in Appendix A, further supporting the GRM's bathymetric computations.

(2) Surface water temperature validation:

The GRM model uses data from the FutureStreams database as input of inflow water temperature, which was validated by Bosman et al (2022). For surface water temperature validation. Figure 2.5 presents a comparison between the simulated and remote sensing temperatures. The GRM model utilizes the LakeTEMP dataset, which is based on the HydroLAKES database and contains surface water temperature data for over 1.4 million lakes worldwide. By matching the GRanD IDs with HydroLAKES IDs, GRM utilizes the primary data from LakeTEMP to analyze and compare the average yearly temperature values for global reservoirs in 2019 (Korver et al., 2024). The R^2 value for surface temperature validation in 2019 is 0.81, and the RMSE is 2.89°C, indicating a strong agreement between simulated and remote sensing data.

Regarding bottom water temperatures, there are currently no suitable long-term measured datasets available for comparison. We explored the use of data from various studies; for instance, one study provided summertime vertical temperature profiles for 153 lakes globally (Pilla et al., 2021). However, upon extracting monthly and yearly averages, we found that these vertical profiles correspond to only a single day within each month, rendering them inadequate for long-term global applications in the GRM model. Moreover, the dataset of 153 lakes offers limited coverage and lacks sufficient representation of reservoirs. Additionally, the current limitation of GRM is its lack of consideration for accurate ice cover simulation in cold regions. Future versions of GRM could incorporate an ice cover model to better capture the hydrodynamic and biogeochemical processes during freezing conditions.

(3) Meteorological Data and Water Discharge:

The water discharge models within GRM are based on the WaterGAP v2.2d dataset, which has been validated by Müller Schmied et al. (2021), ensuring reliable hydrological data for long-term simulations. Similarly, meteorological inputs, such as wind speed and air temperature, are derived

from the ERA5 reanalysis dataset, validated by Hersbach et al. (2020). The integration of these datasets into GRM guarantees high precision in simulating meteorological conditions.

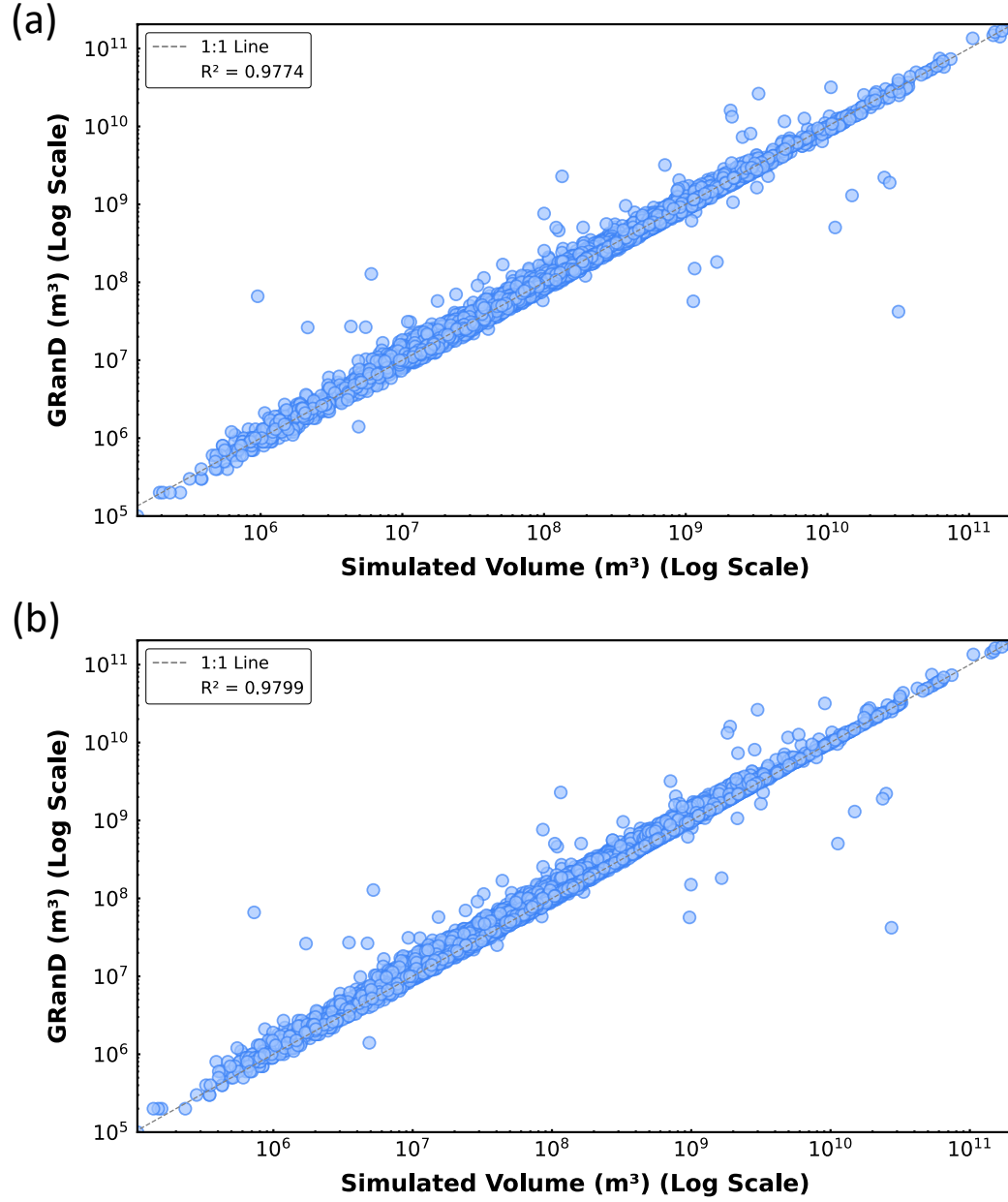


Figure 2.4. Bathymetric data validations for global reservoirs: GRM total volume vs GRanD database total volume; Grey line is 1:1 line. (a) triangular shape (b) rectangular shape.

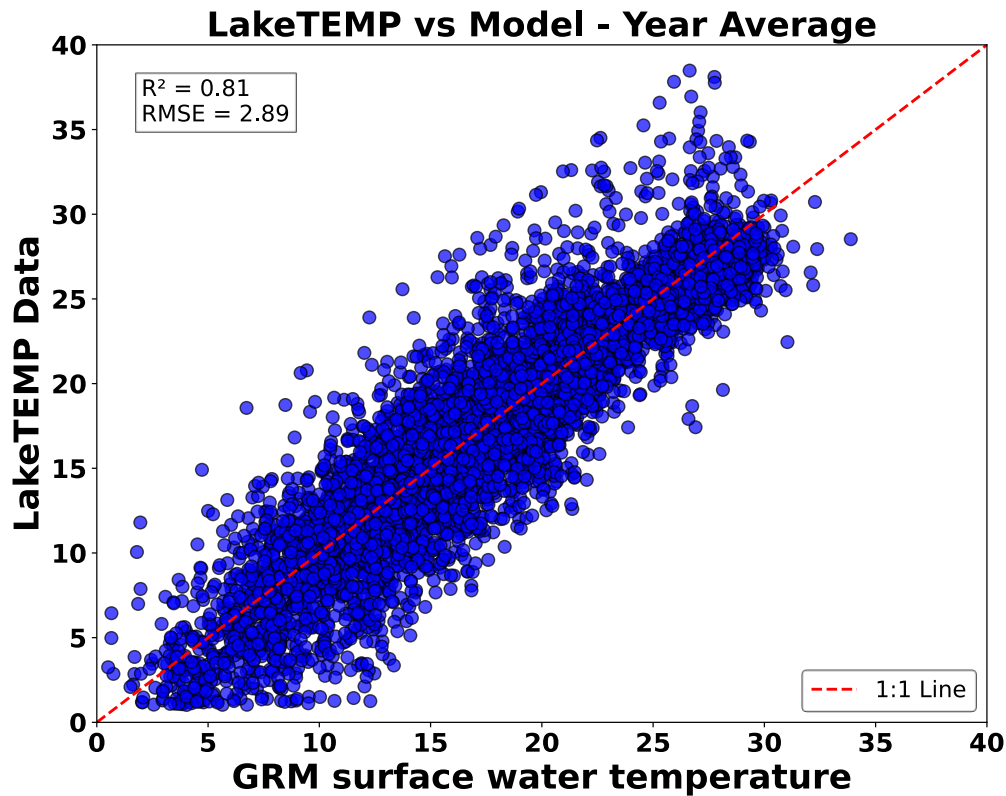


Figure 2.5. Validation of water temperatures for global reservoirs: Surface water temperature comparing with LakeTemp V1.0, 2019 yearly average data are used for comparison (All temperature are showed in °C).

2.6 Data records and data access

The GRM database is designed to be an accessible and user-friendly resource for researchers interested in reservoir hydrodynamics and water quality modeling. Below, we outline the steps for accessing and using GRM.

Accessing the GRM database:

The GRM database is hosted on the FRDR, a Canadian data repository that supports open access to research datasets. FRDR provides a centralized platform for hosting and sharing research data. It operates similarly to platforms like Zenodo or Dryad, offering metadata support and long-term accessibility for research data. Researchers worldwide can access the GRM database at <https://doi.org/10.20383/103.0792>.

Components and files in the GRM database:

Upon accessing the GRM database, users will find several key resources:

Reservoir data files: These include bathymetric data (includes bth_1, bth_2, and bth_3, representing rectangular, triangular, and trapezoidal geometries), water discharge and temperature data, and meteorological inputs. Files are categorized by reservoir ID and year, ensuring straightforward navigation and selection.

Python scripts: Two Python scripts, “GRM_run_public.py” and “GRM_wsc-public.py”, are included to facilitate concurrent simulations and wind coefficient generation.

Control files for CE-QUAL-W2: Model input files compatible with CE-QUAL-W2 are provided, including default parameters and pre-executable files for immediate use.

Documentation: A GRM ReadMe file details the relationships between datasets, file formats, and model implementation steps.

Using GRM for modeling

Download the relevant files: Researchers can download reservoirs specific files (GRM’s IDs are consistent with GRanD IDs) based on their interest and desired simulation years.

Set up the CE-QUAL-W2 model: The GRM outputs are formatted for direct use in CE-QUAL-W2. The provided control files simplify the setup process.

Run simulations: Utilize the included python scripts to run simulations for multiple reservoirs concurrently, optimizing computational resources.

Additional support:

For further details, troubleshooting or updating, users can refer to the GRM documentation or contact the project team at s228yu@uwaterloo.ca. Appendix materials, including additional validation, FRDR usage notes, and usage examples, are also available within the GRM repository.

2.7 Conclusion

In this chapter, I introduce GRM, a new 2-D/3-D modeling database designed for reservoir water quality modeling. GRM bridges the longstanding gaps between global reservoir databases and hydrodynamic modeling, enabling seamless integration of data from established sources like GRanD,

ReGeom, WaterGAP v2.2d, FutureStreams, and ERA5. GRM spans 6,824 reservoirs globally and encompassing multi-decadal data (1980–2019) on water discharge, temperature, and meteorological parameters.

Batch-run CE-QUAL-W2 model simulations, driven by input files from the GRM, quantitatively reveal significant trends in reservoir thermal dynamics. From 1980 to 2019, global average reservoir surface water temperatures increased by 0.47°C per decade, while bottom temperatures rose by 0.1°C per decade. These results align with existing studies and underscore the utility of GRM in capturing depth-specific thermal variations, critical for understanding the impacts of climate warming on aquatic systems. Additionally, GRM demonstrates a strong validation performance, achieving an R^2 of 0.81 for surface temperature simulations compared to remote-sensing datasets.

GRM's simplified bathymetric algorithms and concurrent computing capabilities provide flexibility and efficiency, enabling researchers to adapt it to diverse modeling scenarios. Its design promotes user accessibility while retaining precision, making it a resource for interdisciplinary studies on biogeochemical cycles, nutrient management, and greenhouse gas emissions in reservoirs and downstream ecosystems. Looking forward, GRM offers potential for future enhancements, including integrating ice-cover dynamics and expanding datasets to include additional parameters like nutrient fluxes and carbon budgets. These advancements will further strengthen their role in sustainable water management and climate adaptation strategies, supporting the global effort to balance reservoir development with ecosystem health preservation.

Chapter 3

Changes in thermal structure of reservoirs due to climate change: A global assessment for the period 1980-2019

3.1 Summary

Reservoirs are essential for drinking water supply, irrigation, hydropower, and flood control, yet their thermal dynamics are increasingly altered by ongoing climate change (Maberly et al., 2020; Woolway & Merchant, 2019). In this chapter, the impact of decadal trends in air temperature on reservoir thermal stratification from 1980 to 2019 is simulated by combining ERA5 climate data (Hersbach et al., 2020) with the Global Reservoir Modeling (GRM) database (Yu et al., 2024). The results show that global average air temperature at the locations of the reservoirs included in GRM increased on average by 0.32°C per decade since 1980. Concurrently, global inflow water temperatures to reservoirs also exhibited significant warming trends, with an average increase of 0.59°C per decade as inferred from the FutureStreams database (Bosmans et al., 2022). Model simulations with GRM driven CE-QUAL-W2 reveal a strengthening of thermal stratification, with global mean surface-to-bottom temperature differences increasing from 8.95°C to 10.51°C between 1980 and 2019, which corresponds to an average rate of increase of 0.39°C per decade. This strengthening is primarily driven by the approximately three times faster warming of the surface waters compared to the deeper waters. Moreover, analysis of temperature gradient changes indicates that the global mean thermocline depth has deepened by approximately 1.18 m (about 0.30 m per decade) between 1980 and 2019. This deepening reflects the adjustment of reservoir thermal structure under climate warming, potentially lengthening periods of hypoxia that, in turn, alter the cycling of nutrients in reservoirs, further affecting trophic conditions and aquatic biodiversity.

3.2 Introduction

Reservoirs play significant roles in sustaining human societies by supporting crucial services, such as drinking water supply, irrigation for agriculture, hydropower generation, and flood control (Maavara, Chen, et al., 2020; Winton et al., 2019; Zarfl et al., 2015; Y. Zhang et al., 2023). Globally, there are thousands of large reservoirs, each an integral component of regional water management systems. However, they are increasingly vulnerable to the impacts of climate change, which is rapidly altering the physical, chemical, and biological processes that shape their functionality (Jane et al., 2021; Maberly et al., 2020).

Thermal stratification is common in reservoirs and lakes. It is characterized by the separation of the water column into distinct thermal layers of different water densities (Elçi, 2008; Kirillin & Shatwell, 2016). During warmer months, reservoirs typically exhibit a stratification with warmer, less dense

water forming the surface layer (epilimnion) and cooler, denser water making up the deeper waters (hypolimnion). The intermediate layer, known as the metalimnion or thermocline, is marked by a sharp decline in temperature with increasing depth (Gorham & Boyce, 1989; Woolway et al., 2020). In colder climate regions, inverse thermal stratification may develop when surface water temperature drops below the density maximum of freshwater of 4°C.

Thermal stratification has significant ecological and biogeochemical implications, as it governs the vertical exchanges of solutes, including nutrients and dissolved oxygen (Winton et al., 2019; Wu et al., 2019). These vertical exchanges are influenced by the seasonal stratification regime. In temperate climate regions, a dimictic regime is often observed with two mixing events annually, one following summer stratification and the other following the (inverse) winter stratification. Monomictic lakes and reservoirs experience one annual mixing event, while oligomictic ones mix irregularly and meromictic lakes maintain persistent stratification due to their great depth or the persistence of salinity gradients (Woolway et al., 2020).

Global warming can significantly influence the thermal structure of lakes and reservoirs, with surface freshwater temperatures rising at an average rate of 0.34°C per decade between 1980 and 2009 according to O'Reilly et al. (2015). However, large differences in regional warming are observed because of interactions among local climate factors such as incoming solar radiation, cloud cover, surface albedo, and evapotranspiration rates. For instance, lakes with seasonal ice cover have seen rapid warming at rates of up to 0.72°C per decade due to increased solar radiation and reduced cloud cover, while ice-free lakes have usually experienced slower surface warming (O'Reilly et al., 2015; Sharma et al., 2015).

Lake ecosystems are highly sensitive to shifts in seasonal climate conditions. Spring and summer temperatures in Northern Hemisphere lakes have been arriving earlier since the 1980s, while autumn has been delayed, leading to longer summers (Woolway, Sharma, et al., 2021; Woolway & Merchant, 2019). Specifically, spring and summer have on average advanced by 2.0 and 4.3 days per decade, respectively, while autumn arrival has been delayed by 1.5 days per decade (Woolway, Sharma, et al., 2021). Studies have proposed nine global thermal classes for lakes, each exhibiting unique temperature dynamics (Maberly et al., 2020). By the end of this century, two thirds of lakes are expected to transition to a warmer thermal class under high greenhouse gas scenarios (Maberly et al., 2020).

Despite increasing research on the impacts of climate change, significant knowledge gaps remain regarding how lakes and reservoirs have been responding to climatic change over the past few decades. Most studies have focused on water bodies in the Northern Hemisphere, usually relying on simplified one-dimensional models that do not fully account for the interactions between changes in climate conditions, inflow water temperature and discharge (Jane et al., 2021; Korver et al., 2024; Maberly et al., 2020; O'Reilly et al., 2015; Tong et al., 2023; Woolway et al., 2020; Woolway, Sharma, et al., 2021). O'Reilly et al. (2015) and Sharma et al. (2015) examined changes in summer surface temperature for 292 lakes. Here, we extend the previous work by reconstructing the historical changes in temperature distributions of large reservoirs globally over the period 1980 to 2019, using the GRM driven CE-QUAL-W2 framework introduced in Chapter 2.

3.3 Methods

3.3.1 Modeling framework: GRM and CE-QUAL-W2

GRM comprises information on nearly 7000 reservoirs reported in the Global Reservoir and Dam Database (GRanD) (Lehner et al., 2011). The information is drawn from the following global datasets (Table 3.1): ReGeom for bathymetric data, WaterGAP v2.2d for stream discharge, ERA5 for meteorological parameters (air temperature, wind speed, cloud cover), and FutureStreams for inflow water temperature. The bathymetry of each reservoir in GRM is represented using a simplified triangular geometry and the default 30x30 gridding of depth and length (Yu et al., 2024).

The GRM driven CE-QUAL-W2 simulations were initialized for the year 1980 using the reservoir-specific bathymetric and hydrometeorological data from GRM and, after model spin-up, executed continuously from January 1st, 1980, to day 333 of 2019. The simulation period was truncated at day 333 of 2019 due to limitations in the original WaterGAP v2.2d dataset, which provides discharge data up to that date. CE-QUAL-W2 utilizes daily time series input data, including inflow rates, inflow water temperatures, and meteorological conditions. For input data obtained at originally coarser temporal resolutions (e.g., weekly inflow water temperatures from FutureStreams or monthly discharge from WaterGAP v2.2d), linear interpolation was used to generate daily values. For meteorological input, daily averaged ERA5 data, including air temperature, wind speed, and cloud cover—were used directly. These daily averages were derived from hourly ERA5 observations at 00:00, 06:00, 12:00, and 18:00 Universal Coordinated Time (UTC), ensuring high temporal resolution in capturing diurnal variability without additional interpolation.

CE-QUAL-W2 has been widely applied to simulate coupled hydrodynamics and water quality in diverse reservoirs (Debele et al., 2008; Lindenschmidt et al., 2019; Mi et al., 2020; Noori et al., 2015; Shabani et al., 2017; Shi et al., 2024; Y. Xu et al., 2024; Ziaie et al., 2019). Here, only CE-QUAL-W2's hydrodynamic capabilities were used to generate spatially explicit and time-dependent temperature distributions.

Table 3.1. The summary of input databases.

Contents	Database name (References)	Used Attributes
Reservoir bathymetry	ReGeom (Yigzaw et al., 2018)	Latitude and longitude, dam and reservoir IDs, volume
Meteorological data	ERA5 (Hersbach et al., 2020)	Daily averaged air temperature, dewpoint temperature, wind speed and wind direction, from 1980 to 2019
Inflow water temperature	FutureStreams (Bosmans et al., 2022)	Weekly water temperature, from 1980 to 2019
Reservoir discharge	WaterGAP v2.2d (Müller Schmied et al., 2021)	Monthly discharge at location closest to dam/reservoir, from 1980 to 2019

3.3.2 Vertical water temperature and thermocline depth

The vertical temperature gradients are illustrated here by considering the temperature difference ΔT between the reservoir's deepest (bottom) and topmost (surface) layers. The GRM driven CE-QUAL-W2 simulations were executed continuously from 1980 to 2019 using the multi-threaded global reservoir configurations provided by GRM. Due to computational limitations, presenting the entire dataset—comprising over 30 TB of output—was impractical. Therefore, we selected three representative years (1980, 2000, and 2019) to characterize decadal-scale trends in thermal stratification. Of the 6,824 reservoirs listed in GRM, complete CE-QUAL-W2 output was obtained for 5,420 sites in those three years; the remaining cases lacked depth, and bathymetry information in the source datasets and were not considered further.

To differentiate the reservoirs according to regional climate conditions, we employed the Köppen-Geiger classification system, which distinguishes 30 global climate classes based on a combination of

seasonal temperature and precipitation (Beck et al., 2023). Here, we use a broader climatic grouping by aggregating the 30 classes in Beck et al. (2023) into five major classes, as follows:

- **Tropical:** Classes 1, 2, 3 (616 reservoirs)
- **Arid:** Classes 4–7 (933 reservoirs)
- **Temperate:** Classes 8–16 (2847 reservoirs)
- **Cold:** Classes 17–28 (1017 reservoirs)
- **Polar:** Classes 29, 30 (7 reservoirs)

Note that all the reservoirs in the Polar class are in fact high altitude reservoirs located within mountain ranges. Each reservoir location (latitude and longitude) was aligned with the corresponding Köppen-Geiger raster grid. The resulting climate distribution of the reservoirs is shown in Figure 3.1.

The Python scripts used for data analysis and visualization, including plotting and processing the Köppen-Geiger climate classification, are hosted on a private GitHub repository under embargo until the study is published. Upon publication, the repository will be made publicly available at:

https://github.com/SYubaby/GRM_TemperatureGradient. The Köppen-Geiger climate classification raster data can be downloaded from Figshare at: <https://doi.org/10.6084/m9.figshare.c.6395666.v1>.

The GRM dataset used in this study is hosted on Federated Research Data Repository (FRDR) and can be accessed via DOI: <https://doi.org/10.20383/103.0792>.

The relative importance of input variables on the predicted temperature differences was assessed by Pearson correlation and Bayesian multivariate regression analyses (Hoffman & Gelman, 2014). Statistical analyses were implemented in Python using the PyMC library, which employs Markov Chain Monte Carlo (MCMC) methods for parameter estimation (Salvatier et al., 2016). The temperature simulation results for the years 1980, 2000, and 2019 were downloaded from the corresponding CSV output files of the CE-QUAL-W2 calculations and combined into a single dataset. The analysis was performed for each depth layer (i.e., from top layer_1 to bottom layer_30). Details on the methods are provided in Appendix B.

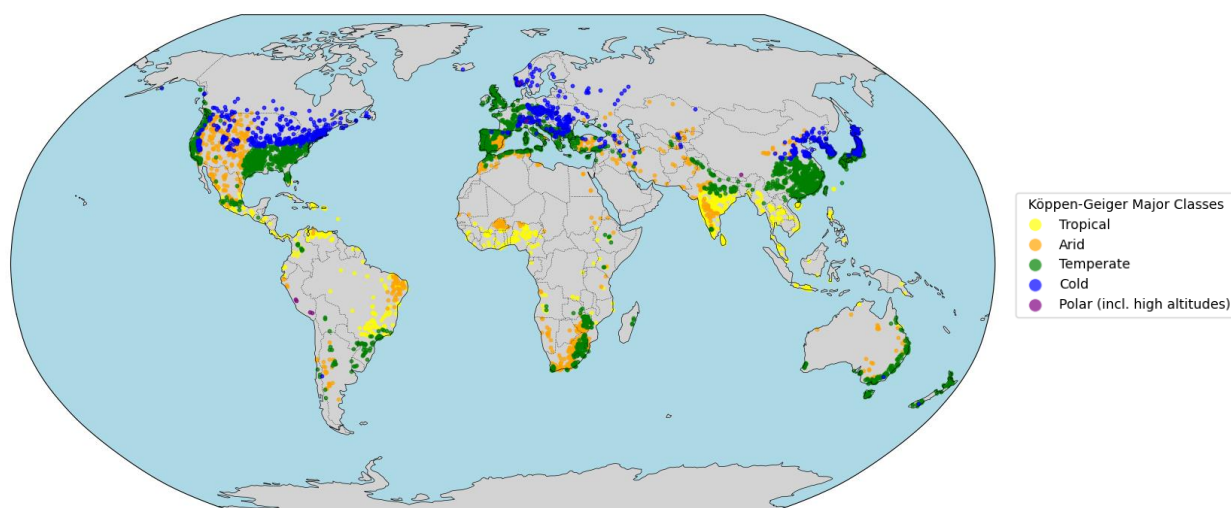


Figure 3.1. Geographical distribution of the GRM reservoirs across the five aggregated Köppen-Geiger classes. See text for the definition of the five climate classes.

3.4 Results

3.4.1 Surface-to-bottom temperature differences

As expected, reservoirs in general experienced a strengthening of their thermal stratification from 1980 to 2019 (Figure 3.2, Figure 3.3, and Table 3.2). The Kernel Density Estimation (KDE) analysis corroborated the generalized strengthening of reservoir water column stratification, with a rightward shift in the ΔT distribution over time (Figure 3.2). The increased standard deviation observed in ΔT (from 5.86°C in 1980 to 5.97°C in 2019; Table 3.2) further implied a growing variability in thermal stratification intensity among reservoirs. The temporal temperature trends reported here highlight the need for deeper investigations into the role climate warming may have been playing in observed ecosystem changes in the world's reservoirs over the past decades.

On average, both surface and bottom water temperatures increased (see Section 3.4.2) but surface water temperature rose faster. The mean annual surface-to-bottom temperature difference (ΔT) increased from 8.95°C (median 8.01°C) in 1980 to 9.38°C (median 8.49°C) in 2000, and further to 10.51°C (median 9.72°C) in 2019 (Table 3.2). This represents an average increase rate of 0.22°C per decade between 1980 and 2000, accelerating to 0.57°C per decade between 2000 and 2019. Over the entire 40-year period, ΔT increased at an average rate of 0.39°C per decade. Additionally, the standard deviation of ΔT slightly increased from 5.86°C in 1980 to 5.97°C in 2019, indicating

growing variability among reservoirs, with some experiencing considerably stronger intensification of stratification compared to others. Collectively, these trends highlighted a significant global pattern of intensifying thermal stratification.

To contextualize the global signal, we aggregated reservoir-level changes by Köppen–Geiger climate zones (Figure 3.3; Table S.1). The increase in the surface–bottom temperature contrast, quantified as $\Delta\Delta T = \Delta T_{(2019)} - \Delta T_{(1980)}$, was positive across all major climate classes. Mean $\Delta\Delta T$ was largest in Cold regions (1.77°C), followed by Temperate (1.57°C) and Tropical (1.51°C) zones, with Arid regions showing a more moderate yet positive change (1.31°C). Changes in Polar regions were small on average (1.37°C) and should be interpreted cautiously due to the limited sample size. The global $\Delta\Delta T$ was 1.56°C (median: 1.41°C), indicating a widespread strengthening of thermal stratification since 1980.

The changes in ΔT also demonstrated distinct geographical patterns (Figure B.1, and Figure 3.3). In 1980, regions exhibiting negligible to very low ΔT values were predominantly located in the coldest climate zones, particularly in the higher latitude regions of Eurasia. However, by 2019, reservoirs in these regions exhibited significant ΔT values. Increases in ΔT were consistent with observed increases in air temperature: averaged over all the reservoir locations, the air temperature rose from 14.99°C in 1980 to 16.27°C in 2019 (Table 3.2), or an average increment of 0.32°C per decade. In parallel, the average dew point temperature rose from 8.72°C in 1980 to 9.50°C in 2019, indicative of a general increase in atmospheric moisture content.

Table 3.2. Summary of annually averaged results with standard deviations (SD) for the three selected years (1980, 2000, and 2019). All units in °C.

Variables / Years	1980	2000	2019
ΔT (mean)	8.95	9.38	10.51
ΔT (median)	8.01	8.49	9.72
SD ΔT	5.86	5.73	5.97
Air temperature	14.99	15.54	16.27
SD air temperature	6.41	5.99	6.17

Dew temperature	8.72	9.30	9.50
SD dew temperature	5.91	5.76	6.10
Inflow water temperature	16.61	17.12	18.95
SD inflow water temperature	6.17	5.78	5.98

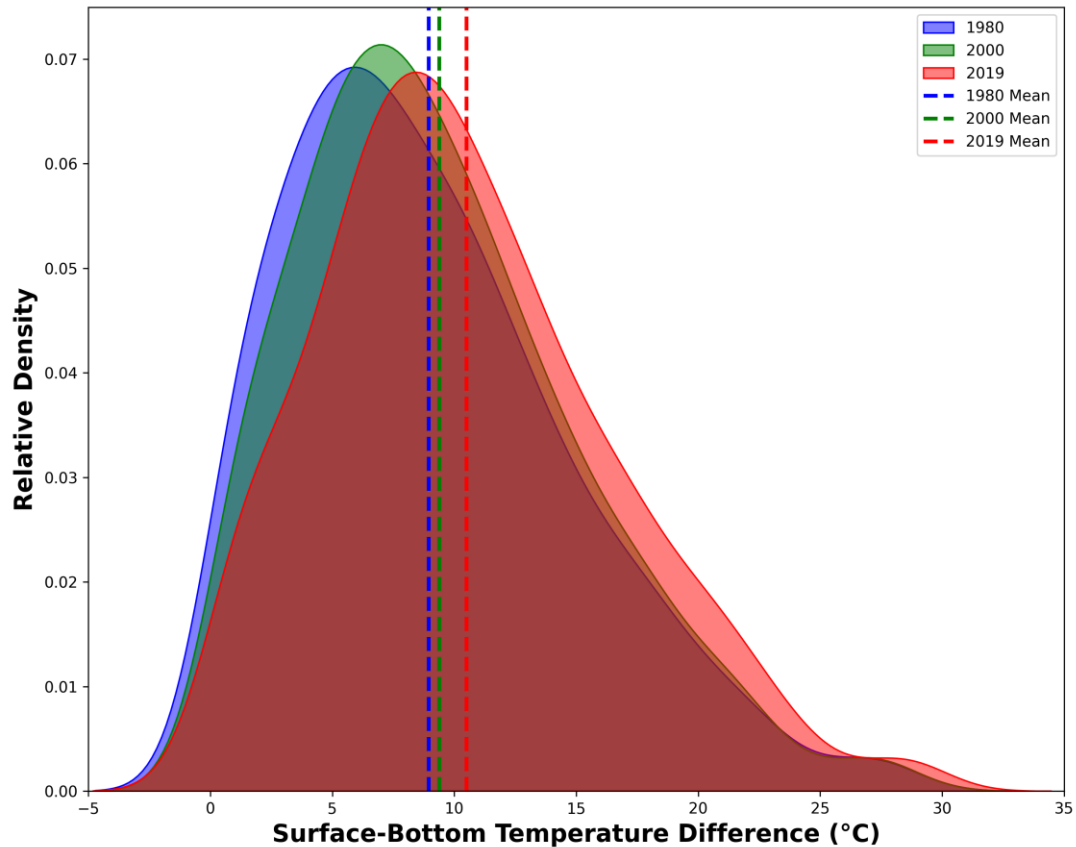


Figure 3.2. Changes in the surface-to-bottom temperature difference (ΔT , $^{\circ}\text{C}$) density distribution of global reservoirs in GRM from 1980 to 2019. The rightward shift over time illustrates a generalized increase in ΔT values driven by global warming.

However, while both the increases in air temperature and reservoir ΔT accelerated after 2000, the dew point temperature's rate of increase slowed down significantly during the 2000-2019 period. Specifically, the dew point temperature increased by 0.29°C per decade from 1980 to 2000 but slowed considerably to 0.10°C per decade between 2000 and 2019. The reasons for the post-2000

dew point temperature deceleration, possibly reflecting shifts in local meteorological conditions, such as reduced humidity inputs or changes in wind patterns, will need further investigation.

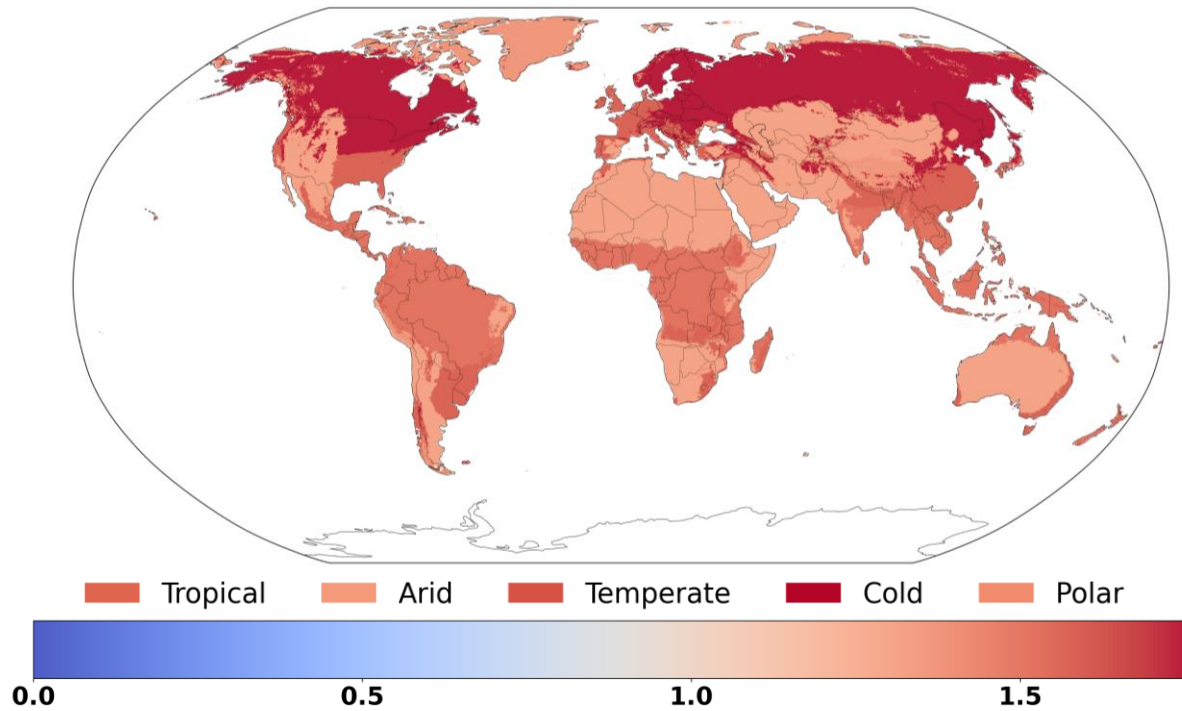


Figure 3.3. Change in the surface-to-bottom temperature difference ($\Delta\Delta T$, °C) between 2019 and 1980 for reservoirs in the GRM. The differences calculated as $\Delta\Delta T = \Delta T_{(2019)} - \Delta T_{(1980)}$; values shown are means aggregated by Köppen–Geiger climate classes. Warmer colors indicate larger increases in ΔT ; Globally, $\Delta\Delta T$ is positive for most reservoirs (mean ≈ 1.56 °C, median ≈ 1.41 °C), indicating a widespread strengthening of the surface–bottom temperature contrast since 1980.

3.4.2 Bottom water temperature changes

From 1980 to 2000 the mean hypolimnetic temperature of global reservoirs increased by $+0.12$ °C (median $+0.09$ °C), indicating a mild right-hand shift visible in the histogram and KDE of ΔT (2000–1980) (Figure 3.4). The response was already climate-dependent: reservoirs in the Cold class warmed by $+0.36$ °C, those in the Temperate class by $+0.08$ °C, whereas Arid and Tropical systems showed virtually no net change and the scarce Polar sites remained near zero.

During 2000-2019 the warming rate almost doubled, with the mean ΔT (2019–2000) reaching +0.24°C (median +0.29°C; Figure 3.4). Warming intensified to +0.65 °C in the Cold class and became unmistakable in Temperate reservoirs (+0.46°C). Meanwhile, reservoirs in the Tropical and Arid classes showed modest negative anomalies, a pattern that may be attributed to stronger deep-mixing events driven by seasonal density inflows in the tropics and frequent draw-down or evaporative cooling in arid basins.

Over the full 40-year period, the global hypolimnetic temperature increase is modest (+0.37°C; ~+0.10°C per decade), yet substantial contrasts emerge among climate classes (Table 3.3). Warming was strongest in Cold-climate reservoirs (+1.00°C; +0.25°C per decade), followed by Temperate systems (+0.54°C; +0.14°C per decade), while the Polar systems exhibited negligible change. These figures confirm that deep-water responses are strongly influenced by background climate and provide a basis for the subsequent analysis of stratification intensification.

Table 3.3. Reservoir hypolimnion water temperature changes (°C).

Climate classes	Bottom water temperature changes (°C)		
	2000–1980 (°C)	2019–2000 (°C)	2019–1980 (°C)
Arid	-0.07	-0.23	-0.30
Cold	0.35	0.65	1.00
Temperate	0.08	0.46	0.54
Tropical	0.13	-0.63	-0.5
Polar*	0.19	-0.27	-0.08
Global	0.12	0.24	0.37

* Polar class contains only 7 sites; numbers are indicative only.

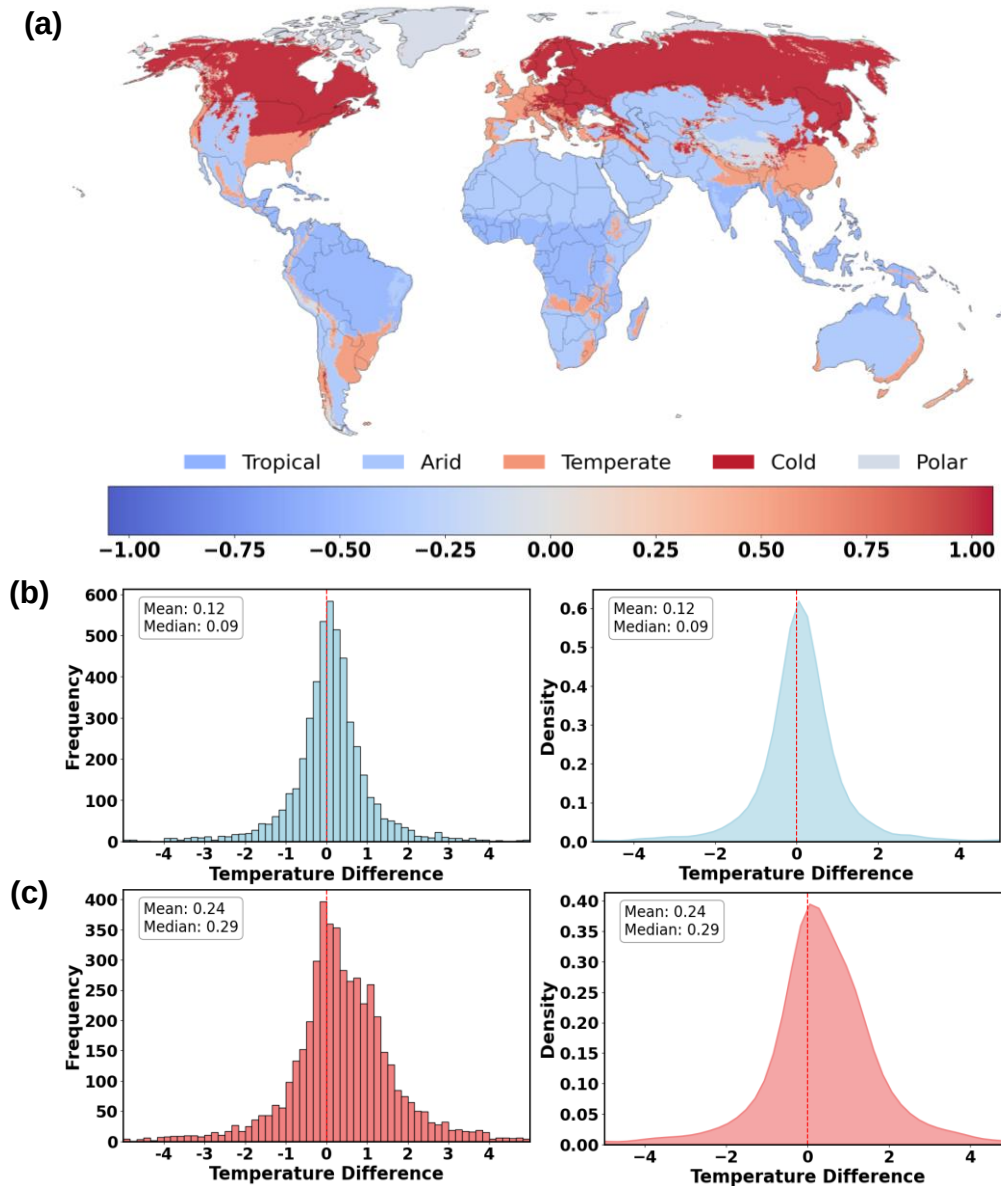


Figure 3.4. Global reservoir bottom temperature differences. (a) Spatial distribution of mean bottom-layer temperature differences between 1980 and 2019, classified by Köppen-Geiger climate zones (Tropical, Arid, Temperate, Cold, Polar); (b) Histogram and kernel density estimate (KDE) showing the distribution of bottom-layer temperature changes between 1980 and 2000; (c) Histogram and KDE showing the distribution of bottom-layer temperature changes between 2000 and 2019.

3.4.3 Thermocline depth

We identified thermocline depth as the midpoint of the layer with the steepest temperature gradient in each reservoir's annually averaged temperature profile (Table 3.4 and Figure 3.5). In 1980, the mean thermocline depth was 15.92 m (median of 12.86 m); by 2019, it had dropped to 17.10 m (median of 13.62 m), that is, an average deepening of 1.18 m over the 40-year period, or approximately 0.30 m per decade.

This long-term trajectory masks sharp regional contrasts. Reservoirs in cold climates exhibited the most pronounced deepening (+2.24 m), followed by those in temperate (+1.44 m) and arid (+0.27 m) zones. Notably, the rate of deepening accelerated substantially after 2000. In cold regions, the decadal rate increased from 0.27 m (1980–2000) to 0.85 m (2000–2019), a more than threefold rise. In temperate zones, the rate escalated from 0.10 m to 0.65 m per decade, around 6.5-fold increase. The global mean followed a similar trajectory, rising from 0.12 m to 0.50 m per decade.

This acceleration signals a structural reorganization of the vertical temperature profile in response to ongoing surface warming. The widening temperature differential between surface and bottom layers enhances thermal inertia and facilitates deeper penetration of stratification. Consequently, vertical mixing is suppressed, and the stability of the water column is reinforced. These patterns reflect a climate-driven downward shift in thermal regimes across global reservoirs.

Table 3.4. Thermocline depth differences between 1980, 2000, and 2019.

Climate classes	Thermocline depth differences		
	2000–1980 (m)	2019–2000 (m)	2019–1980 (m)
Arid	–0.20	0.47	0.27
Cold	0.54	1.71	2.24
Temperate	0.20	1.23	1.44
Tropical	0.43	–1.05	–0.62
Polar*	0.12	–0.19	–0.07
Global	0.23	0.95	1.18

* Polar class contains only 7 sites; numbers are indicative only.

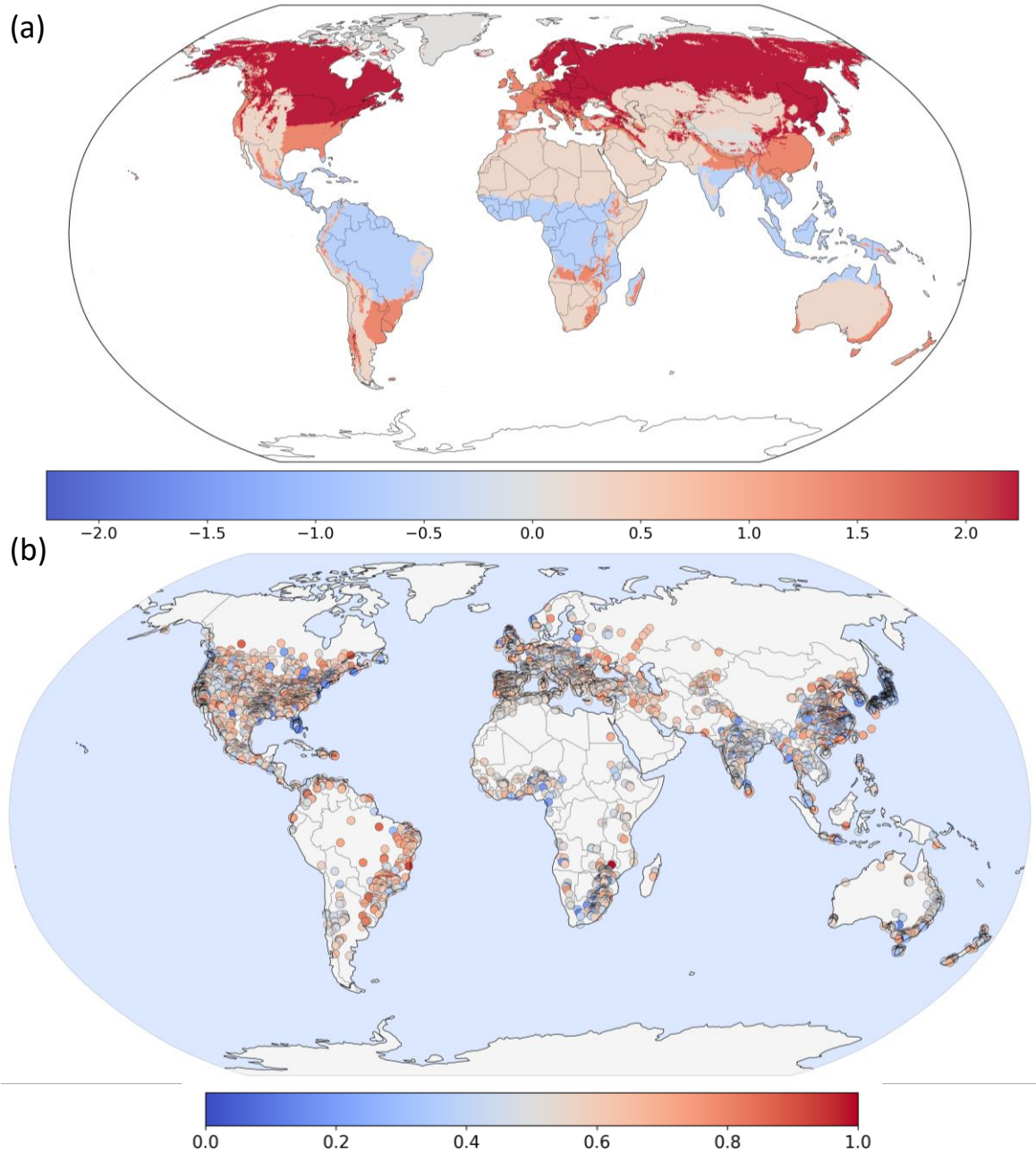


Figure 3.5. Global mean thermocline depth differences and geographical distribution of thermocline depth (log normalized values): (a) mean thermocline depth differences (m) classified by Köppen-Geiger climate zones (Tropical, Arid, Temperate, Cold, Polar), (b) thermocline depth of the year 1980.

3.5 Discussion

This section compares the results obtained here with other global-scale studies to contextualize the model-predicted thermal stratification trends in reservoirs. Overall, our findings on the intensification of thermal stratification, slower bottom water warming, and thermocline deepening align with, and expand upon, existing literature, providing new insights into the impact of global climate change on the thermal dynamics of reservoirs. Additionally, using the Bayesian Markov Chain Monte Carlo (MCMC) method, we gauged the relative importance of the different input data on the temperature predictions for each of the 30 depth layers in the reservoir simulations. Statistical parameters and associated uncertainties are provided to guide future updates and applications by GRM users.

3.5.1 Increasing thermal stratification of reservoirs

Global assessments consistently report significant warming trends of lakes and reservoirs due to ongoing climate change. For example, a global average rate of 0.34°C per decade has been proposed for lake surface water temperatures (O'Reilly et al., 2015), that is, a rate very close to that found in this study for reservoirs. Another study based on a broader dataset of lake surface water temperatures yielded a faster warming rate of $0.44 \pm 0.57^{\circ}\text{C}$ per decade (Zhou et al., 2023). The results of the GRM driven CE-QUAL-W2 simulations also clearly imply a much slower warming of the deeper waters, on average by a factor of about 3-4, compared to the surface waters. To the best of our knowledge, there are currently no global-scale datasets or simulations for bottom water temperature trends in freshwater bodies. In their study, Pilla et al. (2020) analyzed bottom temperature data from 102 lakes and reported an increase of 0.06°C per decade, that is, a rate of similar magnitude as the average decadal rate (around 0.1°C) obtained here for reservoirs of the GRanD database.

Because surface water warming generally outpaces bottom water warming, the surface-to-bottom temperature differences (ΔT) of large reservoirs tend to increase with time, on average by about 1.5°C from 1980 to 2019. This global scale intensification of the thermal stratification of reservoirs is consistent with reports of slower vertical mixing in lakes (Maberly et al., 2020; O'Reilly et al., 2015; Woolway et al., 2020). As further shown by our results, the thermal differentiation of epilimnion and hypolimnion is frequently accompanied by a deepening of the thermocline. It is therefore recommended that future studies examining the changing thermal regime of reservoirs also focus on establishing trends in the depth of the thermocline.

3.5.2 Statistical inferences

The primary input variables to the CE-QUAL-W2 model considered here are air temperature (AT), dew point temperature (DT), and inflow water temperature (IWT). The dependencies of the predicted water temperature distributions on these input variables are assessed by Pearson correlation analysis (Figure 3.6) and Bayesian MCMC regression (Figure 3.7). The two figures illustrate the results for the deepest point of the reservoir (i.e., right upstream of the dam). Note that while the Pearson correlation offers an intuitive assessment of a potential (linear) relationship, Bayesian MCMC provides a more sophisticated framework for examining variable relationships in a multivariate context that accounts for variable interdependencies and uncertainties. For example, one may expect that AT, DT, and IWT have overlapping effects on the reservoir temperature distributions.

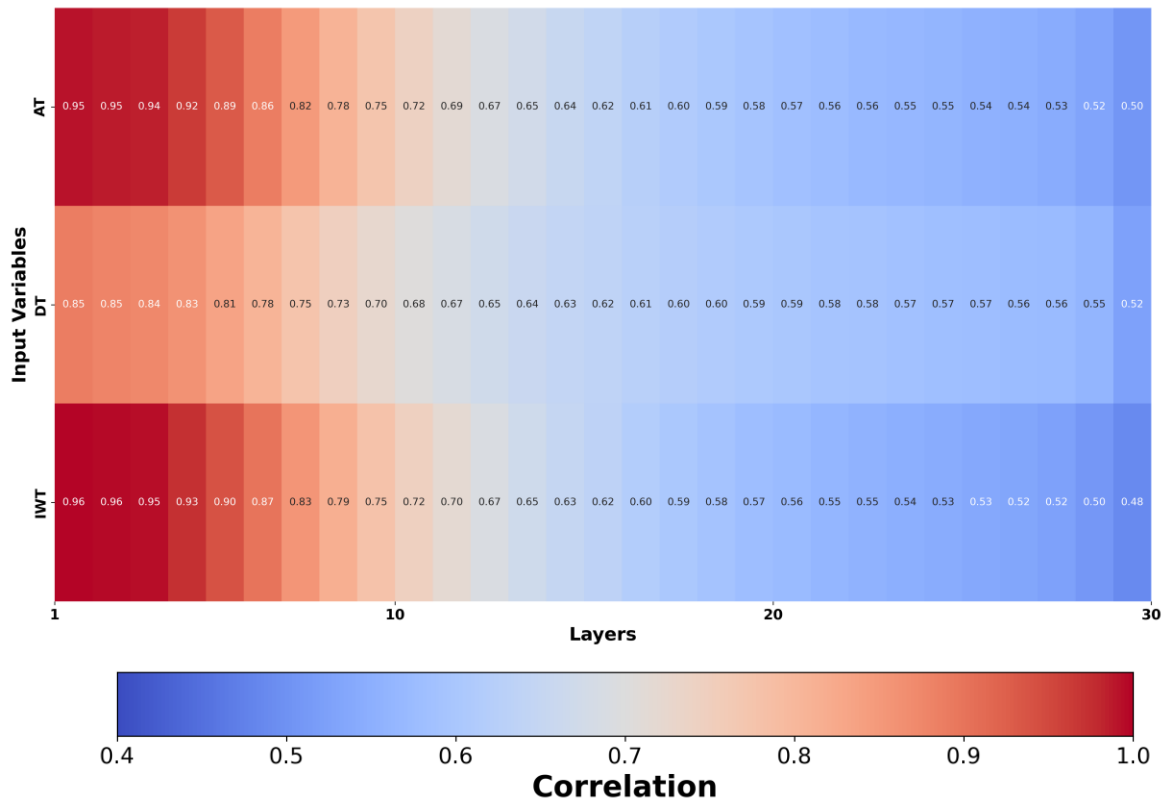


Figure 3.6. Pearson correlation coefficients between 1980, 2000, and 2019 input variables and water temperatures in the reservoir layers averaged over all the reservoirs. Layer 1 is the surface water layer, Layer 30 the deepest layer. The results shown are for the water depth

profile closest to the dam. AT: air temperature; DT: dew point temperature; IWT: inflow water temperature.

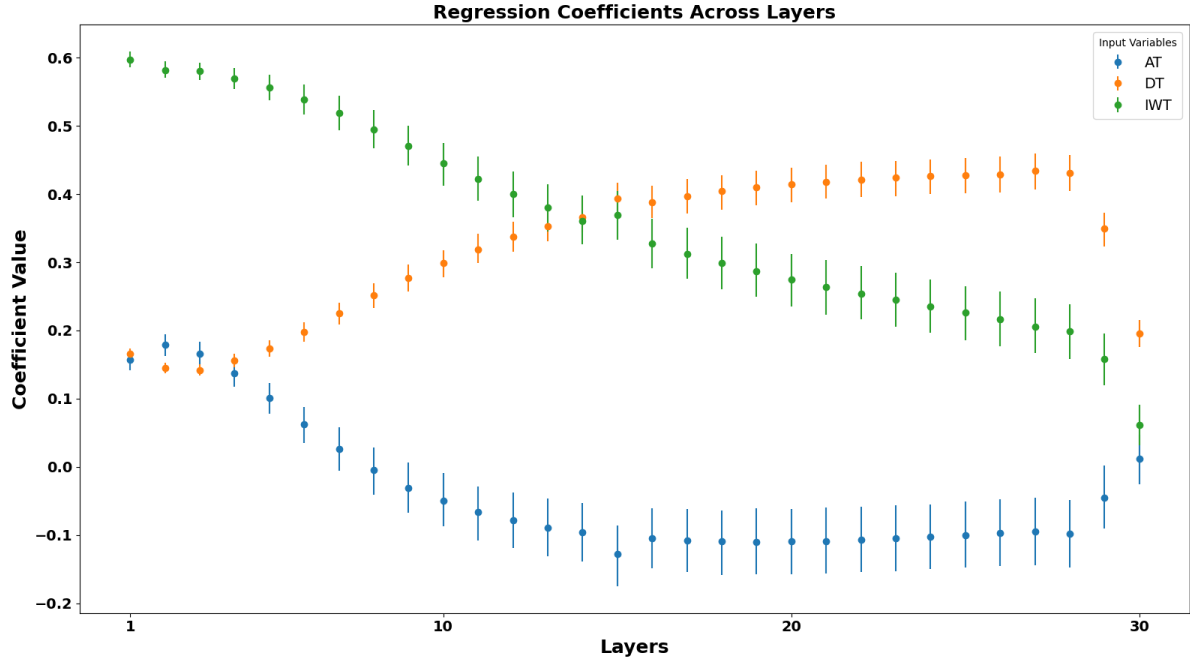


Figure 3.7. Bayesian MCMC regression coefficients relating the reservoir water temperature distribution to the input variables AT, DT, and IWT. The analysis combines data from three years (1980, 2000, and 2019). Error bars represent the 95% high-density interval (HDI) for each coefficient. Air temperature (AT) has a strong positive influence in upper layers, decreasing sharply with depth, while inflow water temperature (IWT) contributes significantly across all depths.

The Pearson correlation results show strong positive relations between the reservoir water temperature in the upper layers (layers 1- 6) and both AT and IWT. With increasing depth, the correlations gradually attenuate. For AT, this finding is not unexpected given that the surface water layer directly modulates the atmosphere-water column interactions (Woolway et al., 2020; Woolway, Jennings, et al., 2021; Woolway, Sharma, et al., 2021). The correlation between the reservoir water temperature distribution and DT is weaker and the attenuation with depth less pronounced.

By distributing shared effects among explanatory variables, Bayesian regression analysis refines the interpretations of the Pearson correlation analysis. The Bayesian regression coefficients for AT

confirm that the air temperature's influence remains primarily confined to the uppermost water layers where coupling with the atmosphere is strongest. The coefficients decrease sharply in deeper layers, reflecting a rapidly diminishing direct impact on water temperature variations. By contrast, the Bayesian regression coefficients for IWT remain high across all layers, consistent with a dominant role of the inflowing water on the thermal conditions across the entire reservoir system. The increasing coefficient values with depth of DT counterbalance the diminishing influence of AT and, to a lesser degree, that of IWT with increasing depth. Similar to IWT, the reservoir's response to DT extends over the entire waterbody.

3.5.3 Some cautionary statements

Several limitations of the current work point to further research efforts that can improve the predictive understanding of the impacts of climate change and human activities on the thermal structure and functioning of reservoirs. The GRM driven CE-QUAL-W2 simulations use a highly simplified reservoir morphology and assume a constant hydraulic residence time by equating inflow and outflow rates. Additionally, the hydrological inputs are derived from WaterGAP v2.2d, which has a monthly resolution (Müller Schmied et al., 2021). These limitations restrict the simulations' ability to capture the effects of short-term changes in water temperature and stratifications, as well as those resulting from water withdrawal events and other anthropogenic impacts, such as seasonal salinization and dam operations (He et al., 2022; Kaushal et al., 2021; Radosavljevic et al., 2022; Z. Xu et al., 2021).

Significant improvements to the work presented here are therefore possible and desirable. More complete information on reservoirs could include details on, for example, the maximum and average water depth, the dam operational regime, and outflow discharge locations. Water quality data, particularly those related to seasonal variations in trophic state and salinity, would help to simulate the temperature distribution of reservoirs more accurately. Furthermore, while many researchers generously contribute to open-source freshwater databases, more effort should be devoted to maintaining and updating these databases.

3.6 Conclusions

Intensification of water column stratification driven by climate change represents a growing risk for freshwater reservoirs. The magnitude of this risk is assessed here by analyzing the temporal trends in the thermal structures of large reservoirs included in the GRanD database using the GRM driven CE-

QUAL-W2 modeling framework. The results show that the surface-to-bottom temperature difference of these reservoirs increased on average from 8.95°C in 1980 to 10.51°C in 2019. The rate of change, however, markedly accelerated after 2000, rising from about 0.22°C per decade (1980–2000) to 0.57°C per decade (2000–2019). The growing surface-to-bottom temperature difference reflects the faster warming of the surface waters of the reservoirs, relative to the deepest layers. Nonetheless, bottom waters also warmed globally by approximately 0.1°C per decade, with faster warming observed in Cold and Temperate climate zones.

The simulation results further indicate a general deepening of the thermocline in reservoirs. On average, the thermocline depth increased from 15.9 m in 1980 to 17.1 m in 2019, hence deepening at an average rate of 0.3 m per decade. The corresponding thickening of the epilimnion further contributes to isolating the hypolimnetic waters and expanding bottom water hypoxia and anoxia that, in turn, can negatively impact water quality and ecosystem health of reservoirs. As a logical next research step, the GRM driven CE-QUAL-W2 calculations will be coupled to Global Climate Model (GCM) projections to simulate potential reservoir evolution scenarios under various Representative Concentration Pathways (RCPs).

Chapter 4

Global Waterbody Calculator: A high-resolution global database of lakes and reservoirs depth-area-volume (D-A-V) relationships

4.1 Summary

The new GLRDAV database assembles key morphometric characteristics for over 1.4 million lakes and reservoirs. By integrating data from HydroLAKES and GLOBathy, > 17 million polynomial (orders 1–5) and power functions describing depth–area–volume (D-A-V) relationships at a 0.1 m depth resolution are presented. The D-A-V relationships are validated against existing databases (ReGeom and GRDL) that provide comparable or simplified global bathymetric relationships, as well as in situ measurements for four waterbodies in the Texas Water Development Board (TWDB). The results show that higher-order polynomial equations (particularly orders 4 and 5) generally yield the lowest RMSE and highest goodness-of-fit (i.e., R^2). Although power functions and lower-order polynomials can offer reasonable representations for simpler and shallower systems, they typically underperform when applied to large or morphologically complex lakes and reservoirs. Our findings underscore the flexibility and robustness of GLRDAV, offering a globally consistent, high-resolution, and computationally scalable resource for hydrological, ecological, and water resource management applications.

4.2 Introduction

Global freshwater bodies, including natural lakes and reservoirs, are important components of the Earth's life-support systems. These water bodies are crucial for maintaining ecological and hydrological balances; they modulate connected river flows and the cycling of nutrients and the mitigation of pollutants (Grill et al., 2019; Pi et al., 2022; Yao et al., 2023). The ecosystem health and storage volume of freshwater lakes and reservoirs, however, vary in response to climate gradients, seasonal weather conditions, as well as increasing anthropogenic pressures (Cooley et al., 2021; Klein et al., 2024; Messenger et al., 2016). For instance, the effects of human activities, from agricultural irrigation and industrial usage to energy generation for urban development, have caused the aggregated storage volume of the world's largest freshwater bodies ($n = 1,972$) to shrink by 53% over the period 1992 to 2020 (Wurtsbaugh et al., 2017; Yao et al., 2023). Beyond water scarcity itself, the detrimental consequences include increased greenhouse gas emissions, biodiversity loss, and negative impacts on human health and well-being. These challenges highlight the urgent need for sustainable management and conservation of freshwater resources (Battin et al., 2023; Harrison et al., 2021; Rosa et al., 2020; Shi et al., 2024; H. Wu et al., 2019).

Models that provide insights into water flow dynamics and water quality of lakes and reservoirs rely on some level of representation of their physical characteristics (J. Bai et al., 2022; Burigato Costa et al., 2019). Among these, the depth-area-volume (D-A-V) relationships help to capture the essential bathymetric features of a water body (An et al., 2022; Busker et al., 2019; Duan & Bastiaanssen, 2013; Hao et al., 2024) that, in turn, play a key role in the coupled hydrological, biogeochemical, and ecological processes regulating aquatic ecosystem productivity, biodiversity, and resource availability (Khazaei et al., 2022; Y. Li et al., 2019). Hence, when integrated with models, current or future, D-A-V relationships can support a wide range of applications (Hao et al., 2024; Y. Li et al., 2019).

Previous research has used a variety of methodologies for acquiring bathymetric and morphometric data of freshwater bodies (Donchyts et al., 2022; Hao et al., 2024; Lehner et al., 2011; Y. Li et al., 2020; Yigzaw et al., 2018). Each method possesses its own strengths and limitations. One major approach involves imagery-based techniques, such as obtained from satellite observations. The latter has a fundamental limitation, however, because it relies on surface water variations, such as changes in water level, to establish elevation-area (E-A) relationships (Y. Li et al., 2019, 2020; Liu & Song, 2022). Therefore, while satellite imagery techniques can systematically yield data for large numbers of water bodies, they are restricted in their capability of characterizing basin morphology beneath the water surface.

Bathymetric data are still mostly derived from direct mapping of the bottom topography of individual lakes or reservoirs. To enable regional and global scale analyses, attempts have been made to assemble this bathymetric information into searchable databases. For example, Lehner et al. (2011) fitted power function relationships between volume, area, and dam height for 6864 reservoirs when developing their Global Reservoir and Dam Database (GRanD). The initial version of GRanD, however, only provides information on the reservoir storage capacities. More recently, GRanD v1.3, which includes 7,320 reservoirs globally, comprises additional attributes by providing not only information on capacity but also on reservoir surface area and dam construction details (Lehner et al., 2011). Along similar lines, ReGeom offers a storage-area-depth dataset for 6,824 major reservoirs using simplified shapes to approximate their surface areas (Yigzaw et al., 2018).

Expanding beyond reservoirs, the HydroLAKES database has mapped shoreline polygons of 1.42+ million natural lakes and artificial reservoirs to generate surface areas (Messenger et al., 2016). HydroLAKES also estimates water residence times and average water depths, although

inconsistencies between the different parameters have been pointed out in some cases (Messenger et al., 2016). The later GLOBathy significantly advanced the bathymetric information content by providing estimates of maximum water depths, bathymetric maps, and D-A-V relationships for over 1.4 million water bodies (Khazaei et al., 2022). However, the dataset suffers from unit inconsistencies and limited depth resolution in D-A-V relationships. More recently, the GRDL database enhanced the depth resolution of D-A-V relationships to 1 m (Hao et al., 2024). However, GRDL only considers reservoirs, and its use requires significant computational resources.

Here, we present a global dataset of D-A-V relationships for over 1.4 million lakes and reservoirs at a depth resolution of 0.1 m. For each water body, the new GLRDAV dataset offers the choice between 12 equations: six depth-area (D-A) and six depth-volume (D-V) equations. Each set of equations comprises five polynomial (first to fifth order) and one power function. Furthermore, for each 0.1 m depth interval within a given water body, the dataset provides the corresponding coefficients for the equations. To support user-friendly data access, we also developed a Python package that streamlines the retrieval of the 17+ million equations and their coefficients.

4.3 Methods and materials

4.3.1 Foundational databases

The databases used for training and validation purposes are summarized in Table 4.1. HydroLAKES and GLOBathy are the primary sources for training data (Khazaei et al., 2022; Messenger et al., 2016). HydroLAKES employs a geostatistical approach to deliver attributes for 1,427,688 waterbodies, including names, locations, volumes, surface areas, and discharge estimates. GLOBathy builds on HydroLAKES using a GIS-based framework, incorporating location and depth information to estimate bathymetric properties and D-A-V relationships for the same set of waterbodies. These datasets serve as the core inputs for constructing the GLRDAV database. Notably, in the original HydroLAKES dataset, the Caspian Sea stands out as the largest saltwater lake, representing approximately 41% of the total volume recorded in HydroLAKES (Messenger et al., 2016).

To validate our results, we employed three independent datasets: ReGeom (Yigzaw et al., 2018), GRDL (Hao et al., 2024), and in situ measurements from the Texas Water Development Board (TWDB; <https://www.twdb.texas.gov/surfacewater/surveys/completed/list/index.asp>). ReGeom provides D-A-V data for 6,824 reservoirs, while GRDL offers high-resolution D-A-V relationships

for 7,250 reservoirs. The TWDB dataset includes observed D-A-V relationships for 121 Texas waterbodies, offering ground-truth reference (Table 4.1).

Table 4.1. Summary of foundational databases for developing GLRDAV.

Databases (References)	Number of waterbodies	Main contents	Limitations	Purpose
GLOBathy (Khazaei et al., 2022)	1,427,688	Name, locations, estimated depth, D-A-V	Wrong units in D-A-V file, simplified depths and D-A-V equations, not applicable for water level fluctuations and other user-defined scenarios	Training and validation
HydroLAKES (Messenger et al., 2016)	1,427,688	Name, locations, volume, surface area, discharge information	Only basic information, no D-A-V	Training and validation
ReGeom (Yigzaw et al., 2018)	6,824	Name, locations, D-A-V	Simplified shapes of waterbodies, data errors	Validation
GRDL (Hao et al., 2024)	7,250	Name, locations, D-A-V	Requires high GPU resources for extended training, heavily depend on precision of the original images, only reservoirs, not user-friendly	Validation
TWDB	121	D-A-V relationships (observations)	Data formats not user-friendly	Validation

4.3.2 D-A-V relationships and 3D visualization

We integrated GLOBathy and HydroLAKES to construct the training dataset. Regression techniques were employed to fit relationships between depth and surface area (D-A), as well as depth and volume (D-V) across more than 1.4 million waterbodies (Figure 4.1). To minimize computational overhead and enable seamless coupling with hydrological models, we approximated high-resolution discrete D-A-V data by fitting continuous polynomial and power-law functions. These surrogate expressions allow rapid estimation of waterbody volumes from water levels in modeling applications. To capture nonlinear dependencies, we employed polynomial and power-law regressions. Polynomial equations ranging from first to fifth order were considered, while power-law equations were fitted using logarithmic transformations. For each waterbody, the D-A and D-V properties were captured by a separate set of five polynomial equations and one power function, together with their corresponding coefficients. For each 0.1 m depth interval, the horizontal surface area and volume are also provided. The approach is formalized by the following equations.

$$y = f(Lat, Lon, x, D_{max}, V_{total}) \quad \text{Equation 4-1}$$

$$y(x) = \begin{cases} a_0 + a_1x + a_2x^2 + \dots + a_nx^n, \\ \alpha x^\beta \end{cases} \quad \text{Equation 4-2}$$

where n is an integer from 1 to 5; y is the dependent variable (either surface area or volume), and x represents water depth measured from the bottom up; α and β are fitted coefficients of the power function. Additionally, we also provide surface area and volume values at 0.1 m increments of depth. The training process further incorporates each waterbody's geographic coordinates (latitude and longitude, consistent with the HydroLAKES database), maximum depth D_{max} and total volume V_{total} , which are extracted from GLOBathy, and HydroLAKES databases.

Python scripts were used to implement the methodology, leveraging Python scientific libraries for efficient data processing and analysis. Pandas were used for handling whole datasets (GLDAV, GLOBathy, and HydroLAKES), Numpy package for the numerical computations, and scikit-learn for the derivation of the regression D-A-V equations. To handle the large number of data, we applied multithreading via concurrent.futures in the ThreadPoolExecutor utility. Interpolation, performed using NumPy, provided the horizontal area and volume estimates for 0.1 m depth interval of a given water body. All scripts, user manuals, and datasets are archived in the Federated Research Data Repository (doi: <https://doi.org/10.20383/103.0881>).

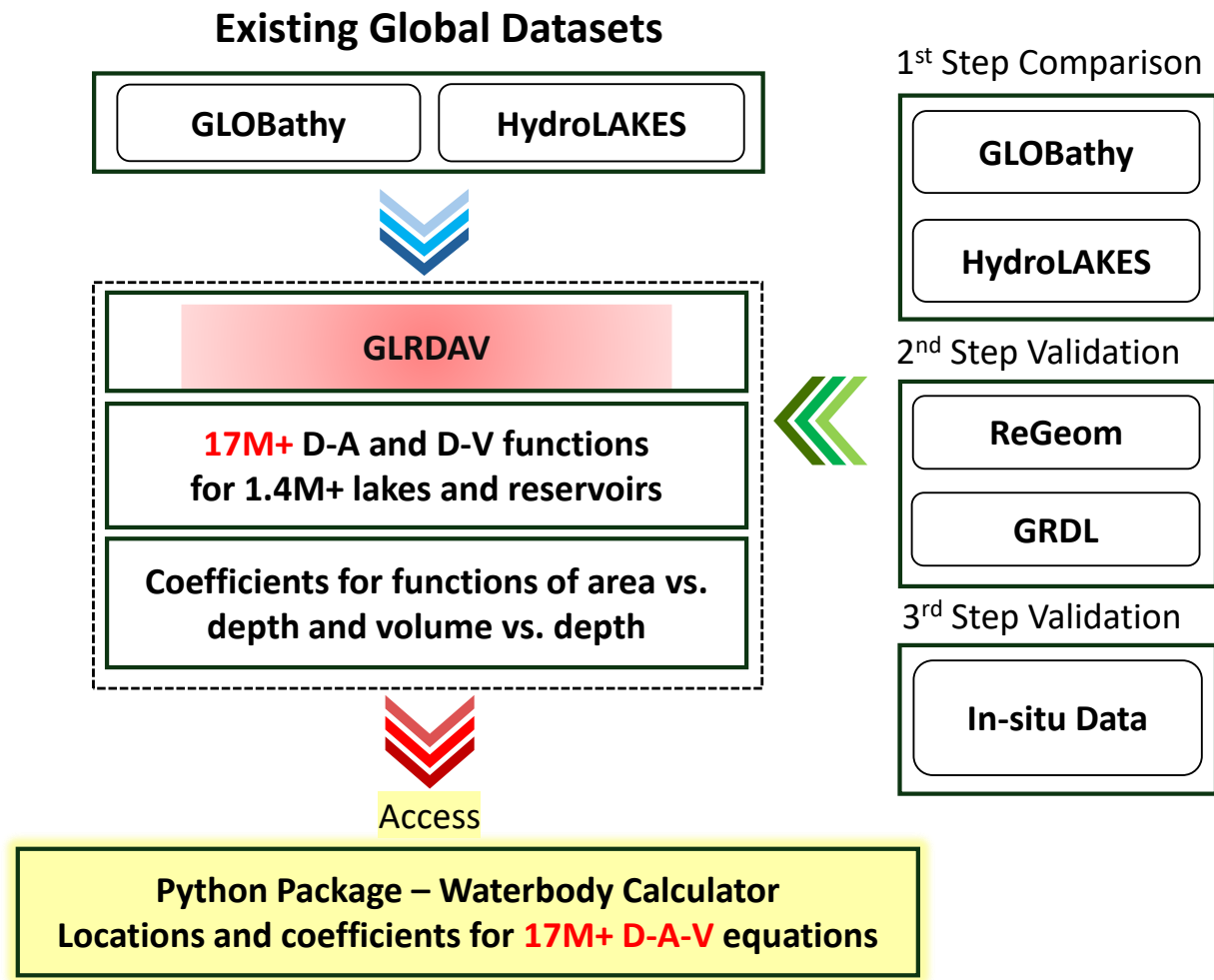


Figure 4.1 Conceptual workflow of the GLRDAV framework. Bathymetric and morphometric data from GLOBathy and HydroLAKES are integrated to derive depth–area–volume (D-A-V) equations, and validated against ReGeom, GRDL, and in-situ measurements.

Bathymetric rasters were produced by remapping calibrated depth–area curves onto a high-resolution grid. Lake polygons from HydroLAKES were first rasterized at 1" (≈ 30 m) resolution, then each water pixel's distance to the shoreline was computed and used to derive its cumulative area percentile. An interpolator built from the normalized depth–area relationship assigned a depth to each pixel, yielding a continuous bathymetry surface. GeoTIFF outputs were subsequently visualized in three dimensions. Full implementation details and code are provided in the Appendix C.

Overall, more than 17 million equations were generated to capture the D-A-V relationships across global lakes and reservoirs. The user accesses the equations via a Python-based tool named “Global Waterbody Calculator,” which organizes waterbody identifiers, geographic coordinates, and model coefficients to facilitate the retrieval of the data and equations (Figure 4.1).

4.3.3 Statistical analysis

To evaluate the accuracy and performance of the derived D–A–V relationships, we employed three primary metrics—coefficient of determination (R^2), mean squared error (MSE), and root mean squared error (RMSE). The same metrics were also used to benchmark our results against three external datasets (ReGeom, GRDL, and in situ data from the Texas Water Development Board, TWDB). These metrics are calculated as follows:

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_{iref} - y_{isim})^2}{\sum_{i=1}^n (y_{iref} - \bar{y}_{ref})^2} \quad \text{Equation 4-3}$$

$$MSE = \frac{\sum_{i=1}^n (y_{iref} - y_{isim})^2}{n} \quad \text{Equation 4-4}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (y_{iref} - y_{isim})^2}{n}} \quad \text{Equation 4-5}$$

where

- n is the number of data points,
- y_{iref} is the i^{th} reference value (from measurements or prior model outputs),
- y_{isim} is the i^{th} simulated value,
- $\bar{y}_{ref}$ is the mean of reference values.

A higher R^2 value signifies that the model effectively explains the variance in the data, while a lower RMSE indicates a closer alignment of the model's predictions with the observed values.

Data filtering and iterative outlier removal

We applied a systematic data-cleaning pipeline to filter out implausible values and extreme outliers that could bias the hydrological characteristics analysis. We began by merging data from HydroLAKES and GLOBathy, matching each record via the unique “Hylak_id” field so that the HydroLAKES’ Shapefile attributes (e.g., average depth, residence time) could be paired with the corresponding GLOBathy’s maximum depth. For every waterbody in this unified dataset, we then computed a depth ratio by dividing the average depth by the maximum depth and classified each entry as either a lake or a reservoir through HydroLAKES’ variables. Next, we excluded all records with ratios ≤ 0 or > 1 , archiving them separately for potential future study. We also removed waterbodies displaying obviously incorrect residence times—specifically, values ≤ 0 or set to -9999 , which “NA” values in original two databases. Many of these extreme residence times arose because the original discharge data used mean flow values, which were often very small, resulting in inflated residence time estimates. Finally, we applied an iterative outlier-removal procedure with a threshold of 1%, discarding only the single highest residence-time entry in each iteration if its removal caused more than a 1% shift in the mean. This process was then repeated until removing another outlier would alter the updated average by less than 1%, thus preventing a small number of extremely large values from disproportionately skewing the entire dataset.

4.4 Results and discussion

4.4.1 Hydrological characteristics analysis of global waterbodies

GLRDAV provides D-A-V equations and associated parameters for 1,427,688 waterbodies worldwide by combining HydroLAKES and GLOBathy records (Khazaei et al., 2022; Messenger et al., 2016). Although many entries exhibit minor inconsistencies for the ratio D_{ave}/D_{max} (e.g., $D_{ave}/D_{max} > 1$), these waterbodies were assigned the maximum depth from the GLOBathy database to ensure that all IDs receive at least one set of D-A-V relationships. In the analyses presented below, however, physically implausible and anomalous data were filtered out. Specifically, 44,588 waterbodies with $D_{ave}/D_{max} \leq 0$ or $D_{ave}/D_{max} > 1$ were flagged, along with additional exclusions based on invalid residence times, and a final iterative procedure removed the most extreme outliers in residence time. After filtering, 1,351,817 waterbodies remained (of which $\sim 99.7\%$ are lakes), forming the core dataset used in this chapter’s hydrological assessments.

Globally (Figure 4.2), there are 1,351,817 lakes and reservoirs, covering a total surface area of $2.525 \times 10^6 \text{ km}^2$ and a volume of $1.485 \times 10^5 \text{ km}^3$, and an average hydraulic residence time of 1,783 days. For reservoirs alone, the average hydraulic residence time is 828 days. North America hosts 958,710 waterbodies, representing the largest count globally, with a total surface area of $1.2 \times 10^6 \text{ km}^2$, a volume of $3.433 \times 10^4 \text{ km}^3$, and an average residence time around 1,642 days (and 1,217 days for reservoirs). Europe, with 261,650 waterbodies, has the highest average residence time of 2,486 days and a total volume of $8.008 \times 10^4 \text{ km}^3$, largely due to the Caspian Sea. Excluding the Caspian Sea reduces Europe's combined volume to $3.688 \times 10^3 \text{ km}^3$. Areal, volume, and residence-time summaries for the other continents are provided in Supplementary Table C.1.

The geographical distribution of the water bodies included in GLRDAV is presented together with their corresponding D_{ave}/D_{max} ratios in Figure 4.2. The D_{ave}/D_{max} values reveal significant regional differences. Higher average ratios reflect flatter lake bottom morphologies, whereas lower ratios correspond to steeper shapes. The waterbodies in North America and Europe have similar mean D_{ave}/D_{max} values of 0.34 and 0.38, respectively. Without the Caspian Sea, the D_{ave}/D_{max} value for Europe remains 0.38. For Asia and Africa, the average ratios are 0.29 and 0.33. South America and Oceania have the lowest mean D_{ave}/D_{max} ratios of 0.26 and 0.24, respectively, reflecting a greater contribution of relatively steeply sloped lakes.

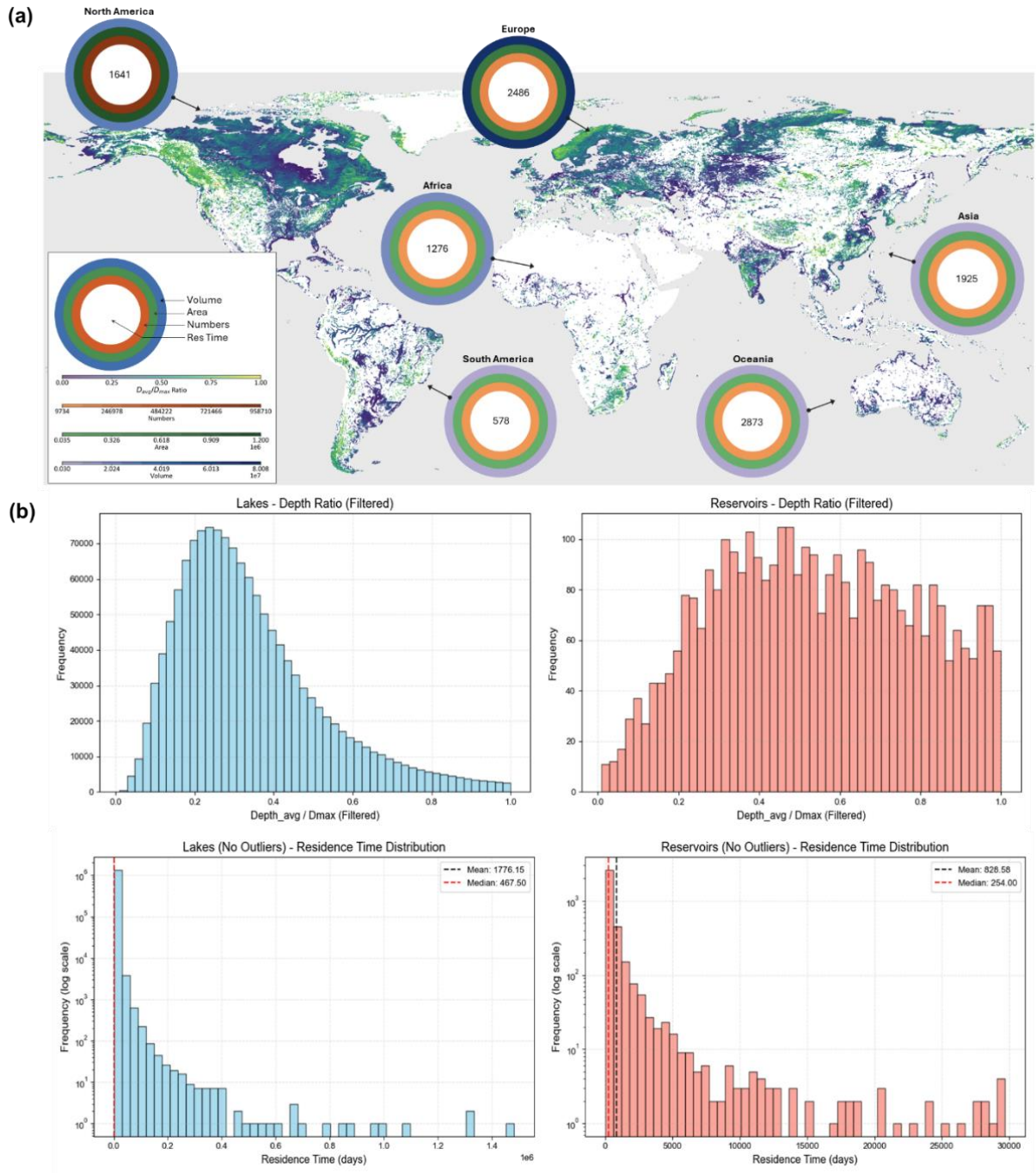


Figure 4.2: (a) Global distribution of lakes and reservoirs. The circles present aggregated indicators for waterbodies by continent: the innermost white ring displays the average hydraulic residence time (days), while the rings denote the number, surface area (km^2), and

volume (km³) of waterbodies with darker colors correlating with higher values. The dots on the map indicate the geographical locations of the waterbodies while the color of the dots scales to the D_{ave} / D_{max} ratio of the water body. (b) Global distributions of the average-to-maximum depth ratio (top panel) and hydraulic residence time (bottom panel) for lakes (blue) and reservoirs (orange), following the removal of physically implausible values and extreme outliers.

4.4.2 D-A-V relationship profile

Each water body in GRLDAV is represented by 12 equations that define its D-A-V characteristics, including six D-A equations and six D-V equations. Each set of six equations encompasses five polynomial functions, spanning first- to fifth-order terms, along with a power function equation. Figure 4.3 illustrates the D-A and D-V relationships for eight randomly selected waterbodies. Additionally, GLRDAV provides for each water body the coordinates (matching those of the ID in HydroLAKES and GLOBathy) and a CSV file with area and volume values for every 0.1-meter depth interval.

Compared to existing databases, GLRDAV offers more user-flexibility and greater depth resolution, while maintaining comparable accuracy. It encompasses smaller water bodies often omitted in earlier datasets, despite their importance in carbon cycling, nutrient dynamics, and climate regulation (Donchyts et al., 2022; Pi et al., 2022). The inclusion of both polynomial and power functions enables the user to choose the option that best fits their application. Although higher-order polynomials (order 4 and 5) generally deliver superior fits, particularly for large or morphologically complex waterbodies, they may yield negative slopes at the lower end of the water depth range, as well as negative A and V values. Alternatively, in certain cases, a combination of equations, say, using the power function at shallower water depths and a higher-order polynomial at greater depths, can produce accurate and physically valid A and V values across the entire water depth range.

When the fitted equations are evaluated against the original GLOBathy and HydroLAKES bathymetry, the mean R^2 exceeds 0.80 and the median RMSE for D-V curves is below 1×10^{-4} km³. Fourth and fifth-order polynomials give the tightest fits, but the power law performs nearly as well for small, shallow lakes. Full error distributions and example plots have been relocated to Appendix C for reference.

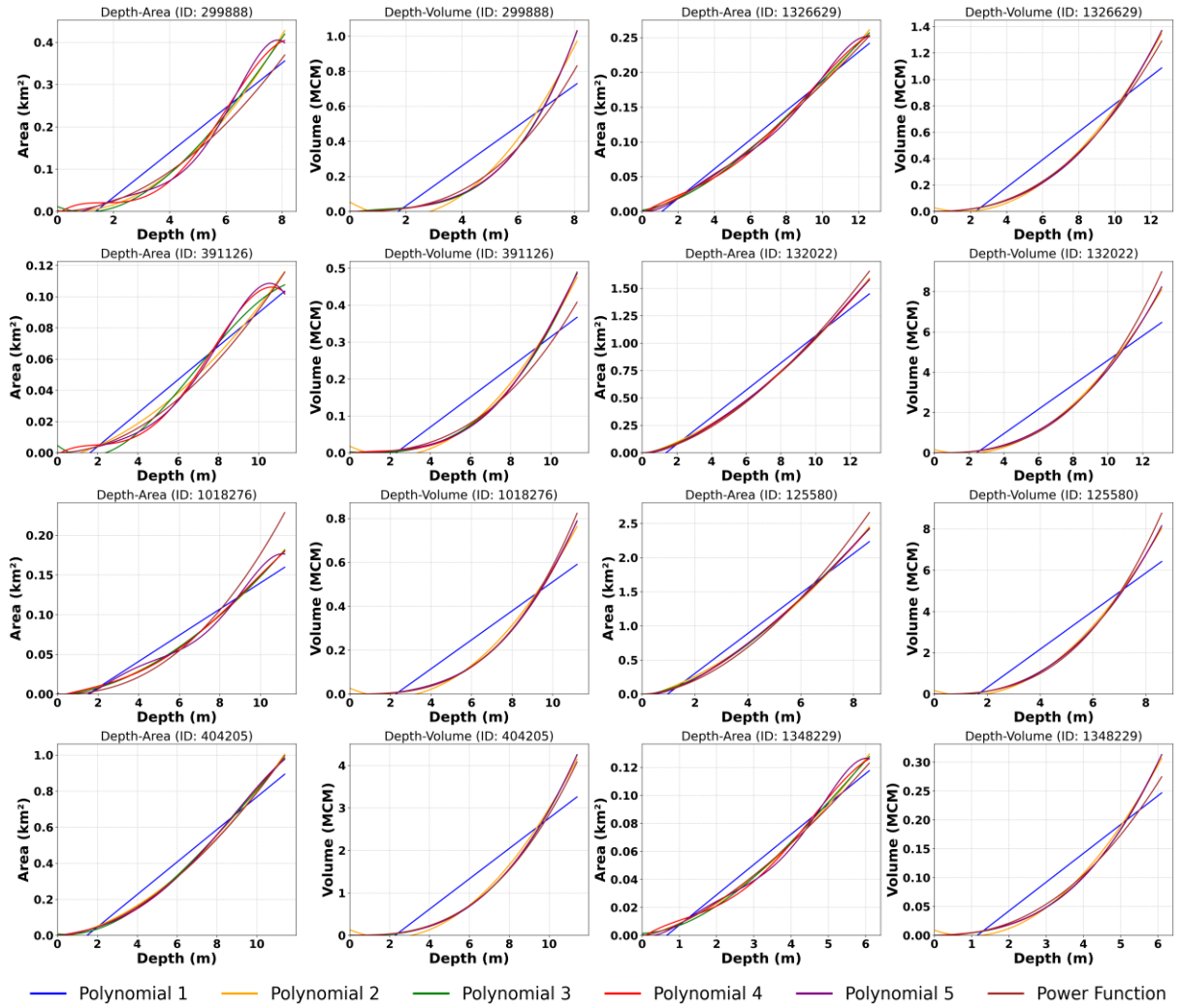


Figure 4.3. D-A and D-V relationships for eight randomly selected waterbodies in GLRDAV. Each panel compares the results of polynomial regressions (orders 1 to 5) and a power function. Polynomial segments that yield negative area or volume are omitted; only physically meaningful depths (≥ 0 m) are shown.

4.4.3 Comparison with ReGeom and GRDL relationships

We validated the GLRDAV-derived D-A and D-V relationships against two independent datasets—ReGeom (Yigzaw et al., 2018) and GRDL (Hao et al., 2024) using RMSE as the evaluation metric. Overall, the models show satisfactory performance, with average D-A RMSE ranging from 27.36 km² up to 35.60 km², and D-V RMSE values spanning 0.192 km³ to 1.213 km³, despite the diverse methodologies used to compile these external databases (Table 4.2).

Table 4.2. Comparative comparison of GLRDAV polynomial (orders 1–5) and power function models against the ReGeom and GRDL datasets. RMSE values are reported for depth–area (D-A) and depth–volume (D-V) relationships, illustrating how each model performs across two independent global waterbody databases.

Metric	Polynomial Function Order 1	Polynomial Function Order 2	Polynomial Function Order 3	Polynomial Function Order 4	Polynomial Function Order 5	Power Function
Validation against ReGeom Dataset						
RMSE (D-A)	27.26	27.87	27.38	27.65	27.60	27.29
RMSE (D-V)	0.650	0.305	0.193	0.192	0.192	0.192
Validation against GRDL Dataset						
RMSE (D-A)	34.29	35.38	35.52	35.60	35.59	35.50
RMSE (D-V)	1.213	1.091	1.043	1.047	1.050	1.057

As summarized in Table 4.2, polynomial models of orders 3, 4, and 5 perform similarly across both ReGeom and GRDL datasets. In ReGeom, their D–A RMSE ranges from 27.38 to 27.65 km², and D–V RMSE from 0.192 to 0.65 km³. In GRDL, the same models yield D–A RMSE between 35.52 and 35.60 km², and D–V RMSE from 1.043 to 1.050 km³. In contrast, the 1st-order polynomial model yields slightly lower D-A RMSE values (27.26 km² for ReGeom and 34.29 km² for GRDL), but it is prone to producing negative predictions—especially in shallow or non-linear segments—due to its intercept term. This limitation underscores the necessity of supplementing low-order models with the power function, which, for ReGeom, achieves the lowest D-A (27.29 km²) and D-V (0.192 km³)

RMSE. Nonetheless, the power function does not consistently outperform higher-order polynomials in all cases, suggesting that a combined approach is preferable.

Although GRDL employs extensive machine learning methods with significant computational resources, its RMSE values for D-A (35.5–35.6 km²) and D-V (1.043–1.213 km³) are comparable to those obtained by simpler polynomial approaches. This indicates that increased computational complexity does not automatically translate to better predictive performance, and it may impede usability in future research. Figures 4.4 and 4.5 illustrate the model performance for randomly selected waterbodies. In the D-A validation (Figure 4.4), higher-order polynomial functions (orders 3–5) provide a closer fit to both ReGeom (orange circles) and GRDL (black circles) outputs, whereas the 1st-order polynomial shows higher deviations—often yielding negative values in shallow areas. The power function, while less precise than the higher order models, remains a robust alternative for waterbodies with simpler bathymetries. In the D-V validation (Figure 4.5), polynomial order 5 consistently achieves the lowest RMSE, although the power function remains competitive in some cases. Figure 4.6 presents scatter plots of log (RMSE) values for D-A and D-V relationships across the whole ReGeom and GRDL waterbodies. The data points reveal that while the 5th-order polynomial generally attains lower errors overall, the power function has less complex D-A-V dynamics. By contrast, the 1st-order polynomial exhibits larger deviations, particularly for deeper or irregular waterbodies. Additionally, the upward trend in RMSE with increasing depth underscores the difficulty of capturing complex bathymetries using a single functional form, thereby reinforcing the importance of combining multiple model types to accommodate diverse underwater topographies.

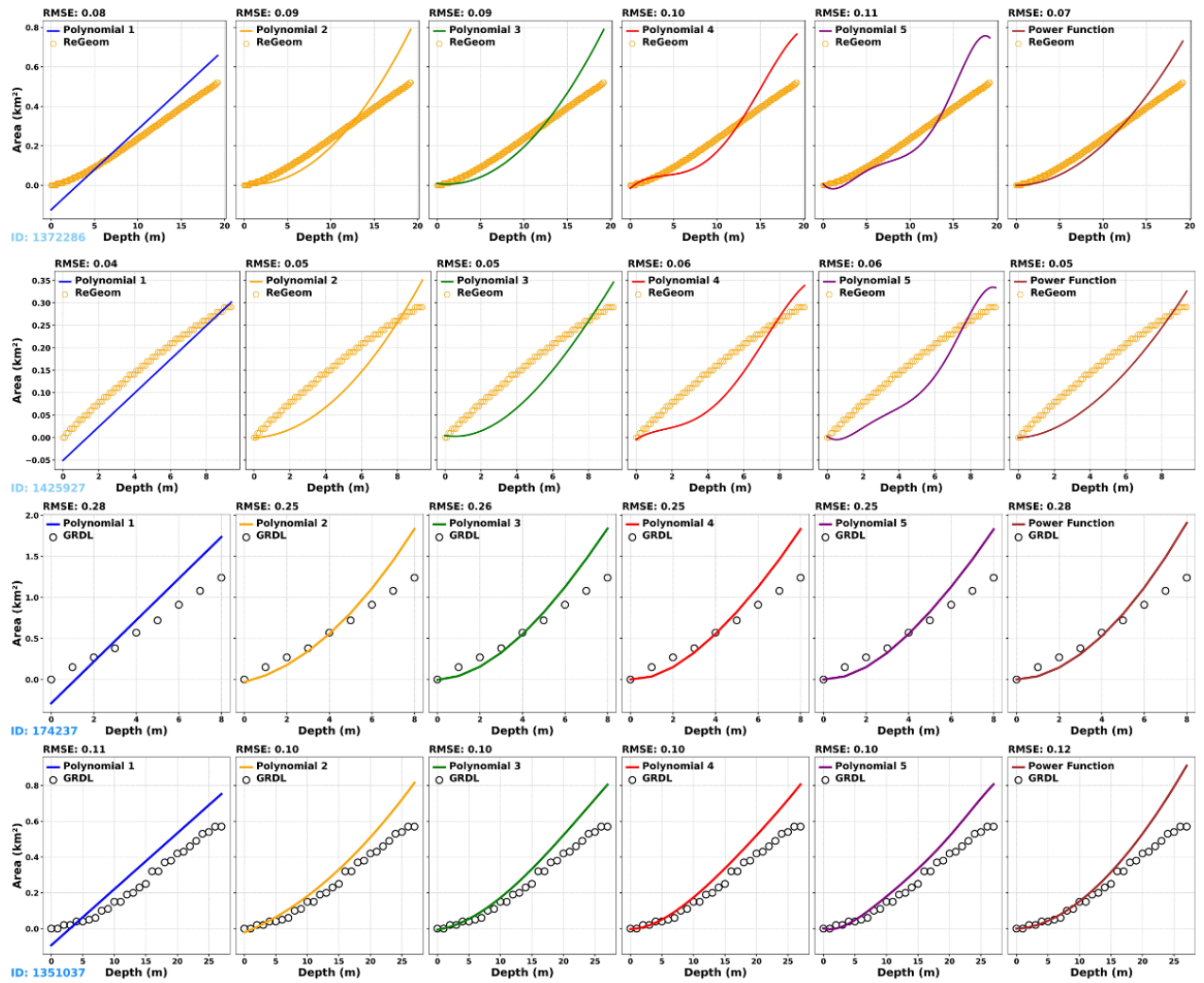


Figure 4.4. Comparison of the depth–area (D-A) relationship against the ReGeom (orange circles) and GRDL (black circles) datasets for selected waterbodies (ID in blue text).

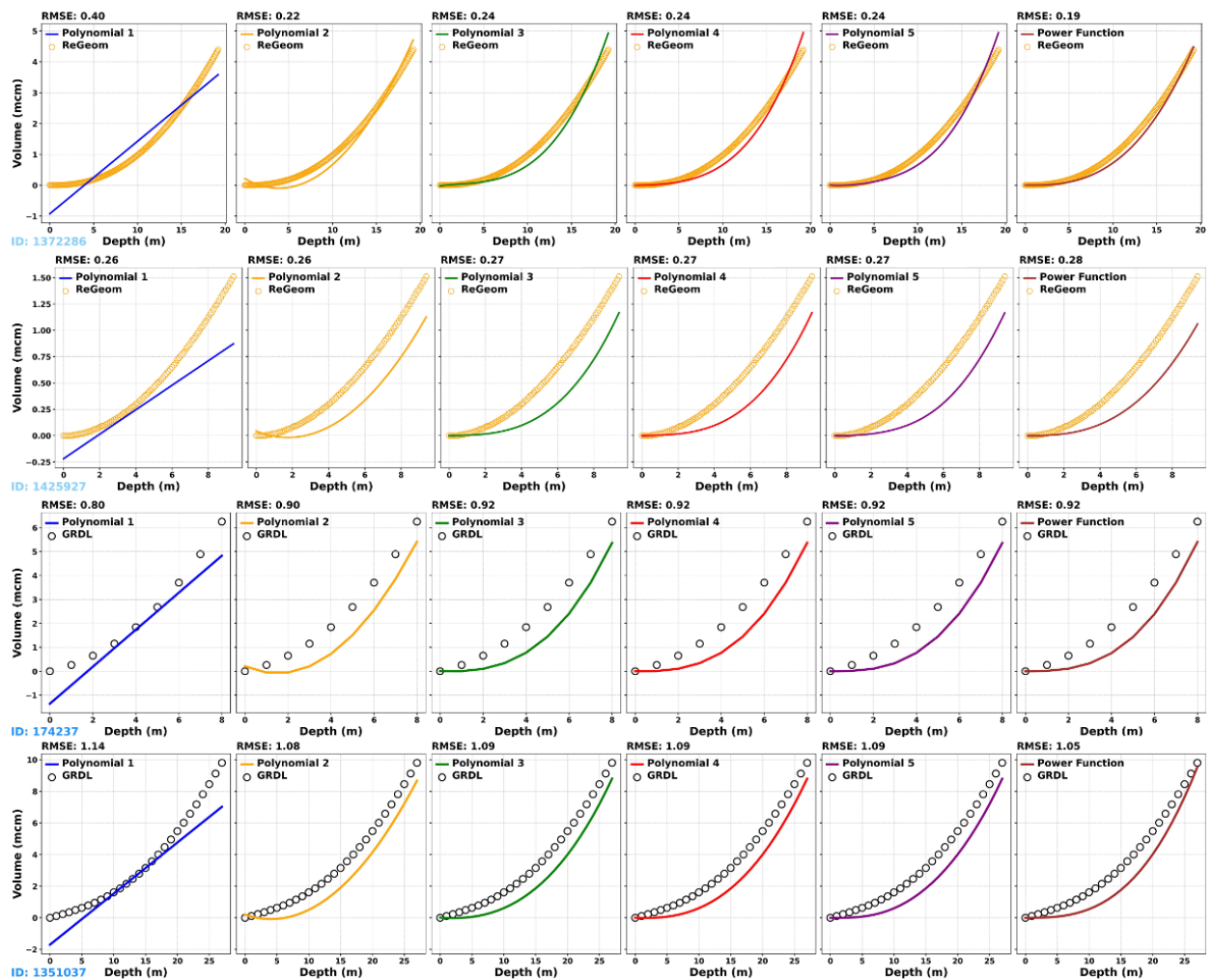


Figure 4.5. Comparison of the depth–volume (D-V) relationship against the ReGeom (orange circles) and GRDL (black circles) datasets for selected waterbodies (ID in blue text).

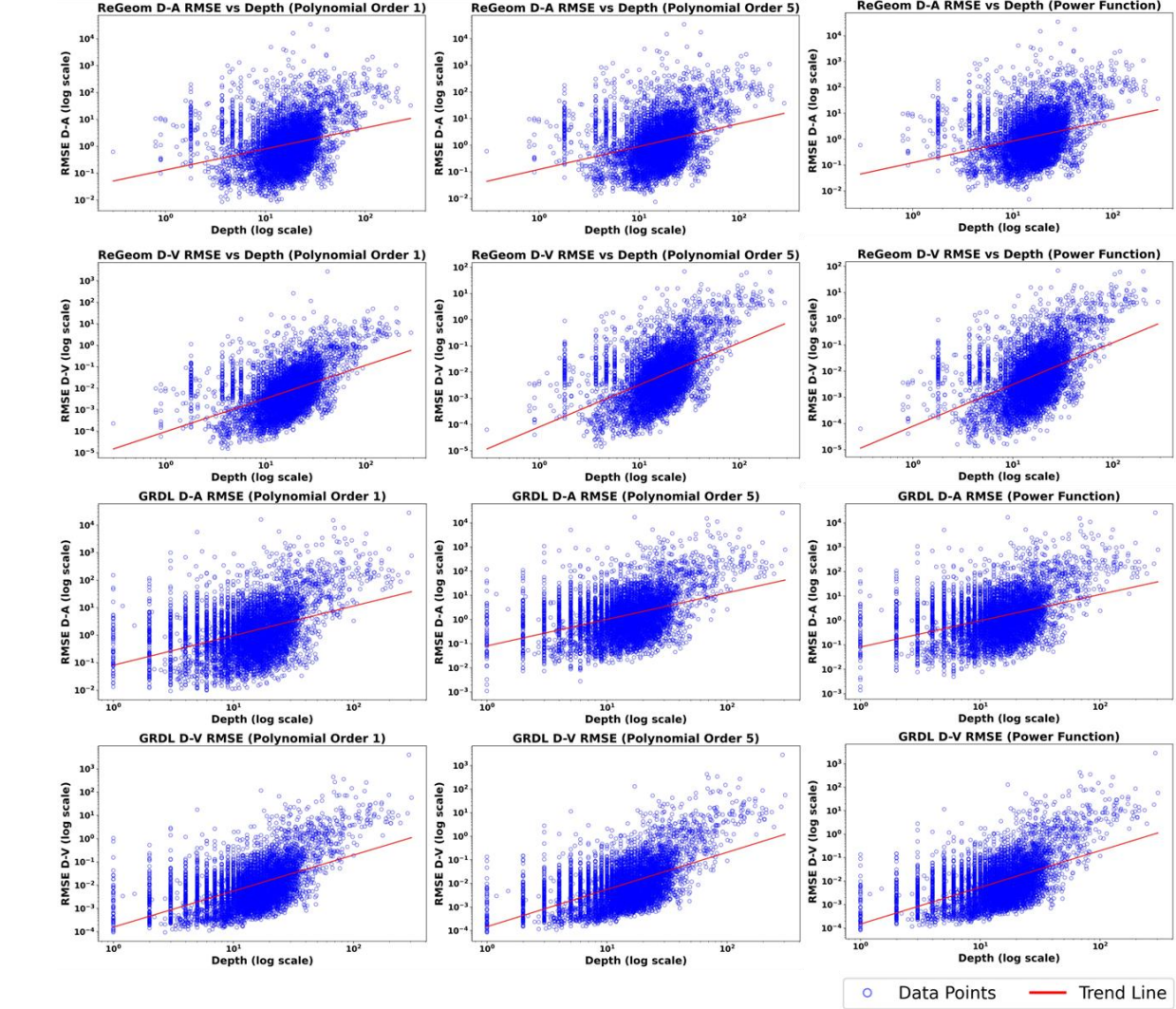


Figure 4.6. Scatter plots of RMSE (log scale) values for D-A and D-V relationships of ReGeom and GRDL waterbodies, models of polynomial orders 1 and 5, and power function included.

4.4.4 Comparison with in-situ data

To test the performance of the GLRDAV-derived D-A-V relationships, we compared model predictions with in-situ measurements from the Texas Water Development Board (TWDB; <https://www.twdb.texas.gov/surfacewater/surveys/completed/list/index.asp>). Four waterbodies—Cedar Creek, Coleman Reservoir, Hubbard Creek, and Lake Whitney—were selected for analysis because they are included in all datasets. For each waterbody, predictions from GLRDAV (using polynomial functions of orders 1–5 and a power function) were compared against results from ReGeom and GRDL (Figure 4.7).

(1) Cedar Creek: for the D-A relationship, Table C.2 shows that the GRDL model yields an RMSE of 23.0 km² ($R^2 = 0.73$), while the ReGeom result is slightly improved (RMSE = 16.9 km², $R^2 = 0.85$). In contrast, the GLRDAV models based on polynomial functions of orders 2–5 achieve RMSE values of 11.9 km² with R^2 values close to 0.93, representing an improvement of approximately 35% in RMSE compared to both GRDL and the power function (which has an RMSE of 18.3 km² and R^2 of 0.83). For the D-V relationship, GRDL performs very poorly (RMSE = 0.248 km³, $R^2 = -0.044$), while ReGeom gives a considerably better result (RMSE = 0.065 km³, $R^2 = 0.93$). Here, the GLRDAV higher-order polynomial models (orders 3–5) produce RMSE values of about 0.079 km³ with R^2 near 0.90, whereas the power function's RMSE is 0.114 km³ ($R^2 = 0.78$).

(2) Coleman Reservoir: our results indicates that for the D-A relationship, the GRDL model is highly inconsistent (RMSE = 2.3 km² with a negative R^2), while ReGeom achieves an RMSE of 0.65 km² ($R^2 = 0.60$). Notably, the GLRDAV 1st-order polynomial model delivers the best performance (RMSE = 0.4 km², $R^2 = 0.83$), with the power function (RMSE = 0.6 km², $R^2 = 0.62$) and other polynomial orders showing slightly higher errors. In the D-V relationship, GRDL again shows abnormal results (RMSE = 0.014 km³, $R^2 = -10.22$), and ReGeom obtains an RMSE of 0.004 km³. Meanwhile, the GLRDAV polynomial models (orders 2–5) yield RMSE values in the narrow range of 0.0023–0.0024 km³ with R^2 values around 0.68–0.69, outperforming both GRDL and the power function (RMSE = 0.0024 km³, $R^2 = 0.67$) (Table C.3).

(3) Hubbard Creek: As shown in Table C.4, for the D-A relationship, the GLRDAV power function stands out with an RMSE of 1.9 km² and an R^2 of 0.95, whereas the polynomial models (orders 1–5) yield RMSE values around 5.5 km² and R^2 values near 0.61. For the D-V relationship, although the

higher-order polynomial models (orders 3–5) achieve RMSE values around 0.007 km^3 with R^2 near 0.96, the power function produces an even lower RMSE of 0.005 km^3 and a higher R^2 of 0.98, indicating very good performance in this case.

(4) Lake Whitney: Table C.5 provides that for the D-A relationship, the power function again performs best with an RMSE of 1.4 km^2 and an R^2 of 0.72, slightly outperforming the GRDL model (RMSE = 1.5 km^2 , $R^2 = 0.71$) and the polynomial models (RMSE = 1.6 km^2 , $R^2 = 0.65$). In contrast, for the D-V relationship, GRDL exhibits the lowest RMSE at 0.002 km^3 with an R^2 of 0.96, while the power function achieves an RMSE of 0.003 km^3 ($R^2 = 0.95$) and the polynomial models (orders 2–5) have higher RMSE values around 0.004 km^3 ($R^2 = 0.87$).

These comparisons demonstrate that the performance of the GLRDAV models varies with waterbody D-A-V relationship. In general, for waterbodies such as Cedar Creek and Coleman Reservoir, higher-order polynomial models (orders 3–5) consistently provide well performance, reducing RMSE by up to 35% compared to other models and outperforming ReGeom and GRDL. However, for Hubbard Creek and Lake Whitney, the power function occasionally delivers better results for one or both relationships. Overall, while the power function has been widely used in prior studies, our analysis shows that its performance is comparable only to that of the 2nd-order polynomial; in most cases, higher-order polynomial models yield greater accuracy and stability. Additionally, the external datasets GRDL and ReGeom exhibit notable inconsistencies, with GRDL showing extremely poor performance for certain waterbodies. Thus, the GLRDAV framework’s flexibility—offering multiple functional forms—enables users to select the optimal model based on specific waterbody characteristics, such as water bodies’ IDs and user defined depth.

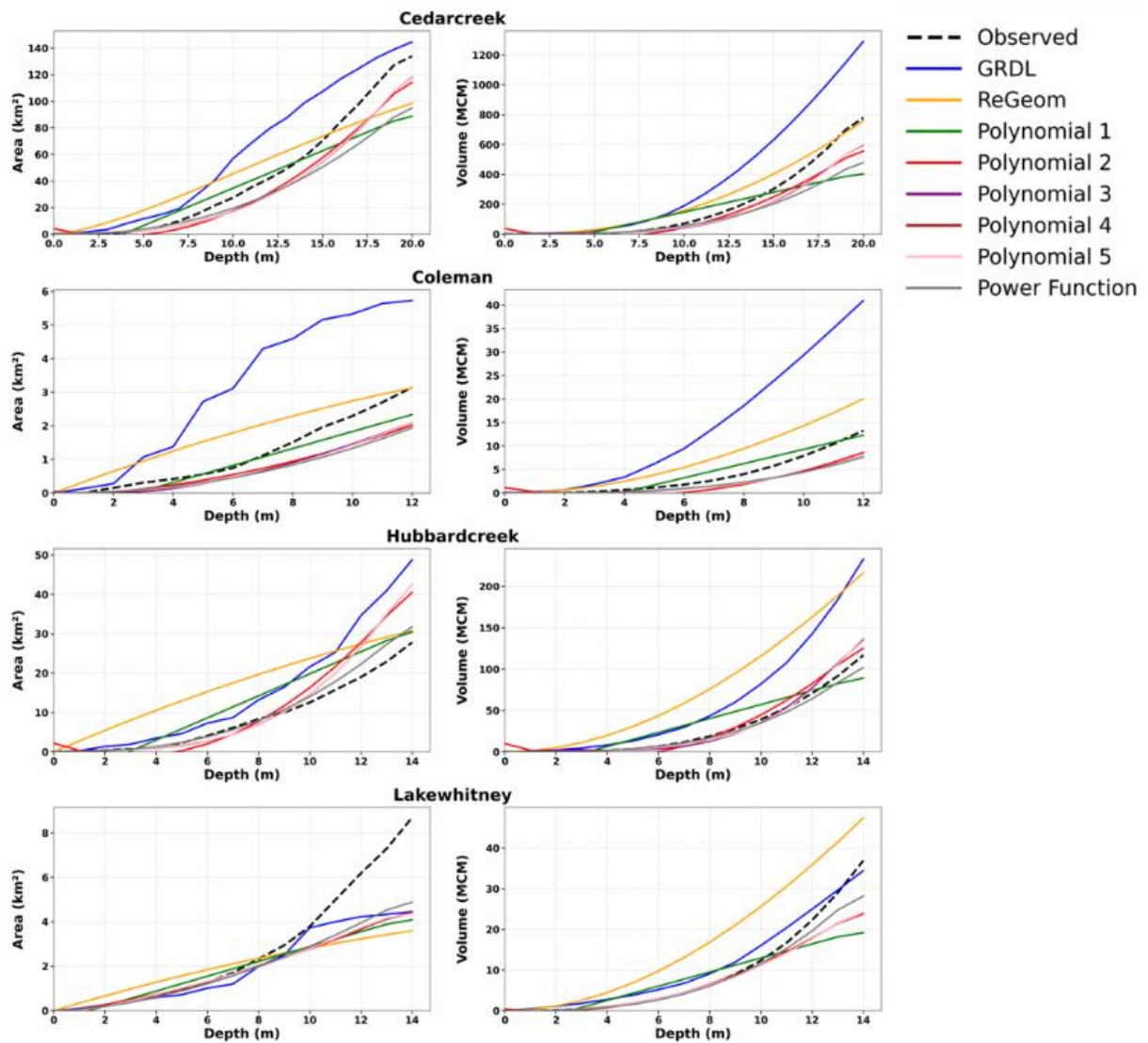


Figure 4.7. Comparison of GLRDAV equations (polynomial orders 1–5 and power function) and ReGeom and GRDL models versus in-situ data-based D-A and D-V relationships for four waterbodies in Texas (Cedar Creek, Coleman Reservoir, Hubbard Creek, and Lake Whitney). In general, GRDL and ReGeom exhibit poorer fits to the observed relationships. Note that none of the model equations capture the pronounced change in slope of the observed D-A curve of Lake Whitney.

4.4.5 Global Waterbody Calculator usage note and examples

To streamline the application of the GLRDAV equations in water quality modeling and future studies, we developed a Python package called “Global Waterbody Calculator” (Figure 4.8). This package, available via PyPI, integrates several libraries—SymPy for symbolic equation parsing, Geopy for distance-based queries, Pandas for data handling, and Matplotlib for visualization. Once installed, users can specify water bodies either by their unique IDs (consistent with HydroLAKES IDs) or by latitude and longitude coordinates. If only coordinates are provided, the tool automatically identifies the nearest water body using geospatial distance calculations.

After selecting the waterbodies of interest, the package computes D-A and D-V relationships using the polynomial (orders 1–5) and power function coefficients derived from GLRDAV. Results are presented as Pandas DataFrames and can be exported to CSV files for further processing. The package also generates optional plots showing how area and volume vary with depth, typically at 0.1 m increments. This functionality supports both single-waterbody analyses and batch processing for larger datasets, enabling efficient exploration of hydrological and ecological scenarios on regional or global scales.

To illustrate how the GLRDAV equations can be converted into spatially explicit bathymetry, we reconstructed 3-D maps for four water bodies—Lake Erie, Cedar Creek Reservoir, Lake Ontario, and Lake Diefenbaker—using the “Global Waterbody Calculator” (Figure 4.9). The resulting surfaces capture each basin’s distinctive bathymetric signature—Erie’s broad littoral shelves, the steep dendritic arms of Cedar Creek, Ontario’s twin basins and the pool-riffle rhythm of Lake Diefenbaker—delivering the spatial fidelity required for process-based models, in which shoreline geometry shapes wave energy and resuspension while bottom slope governs deep-water circulation and nutrient exchange. By automating this reconstruction, the calculator removes a long-standing barrier to basin-scale assessments and opens the GLRDAV framework to wider applications, from mapping pollutants distributions and delineating critical habitats to tracking climate-driven shifts in water storage across thousands of lakes worldwide.

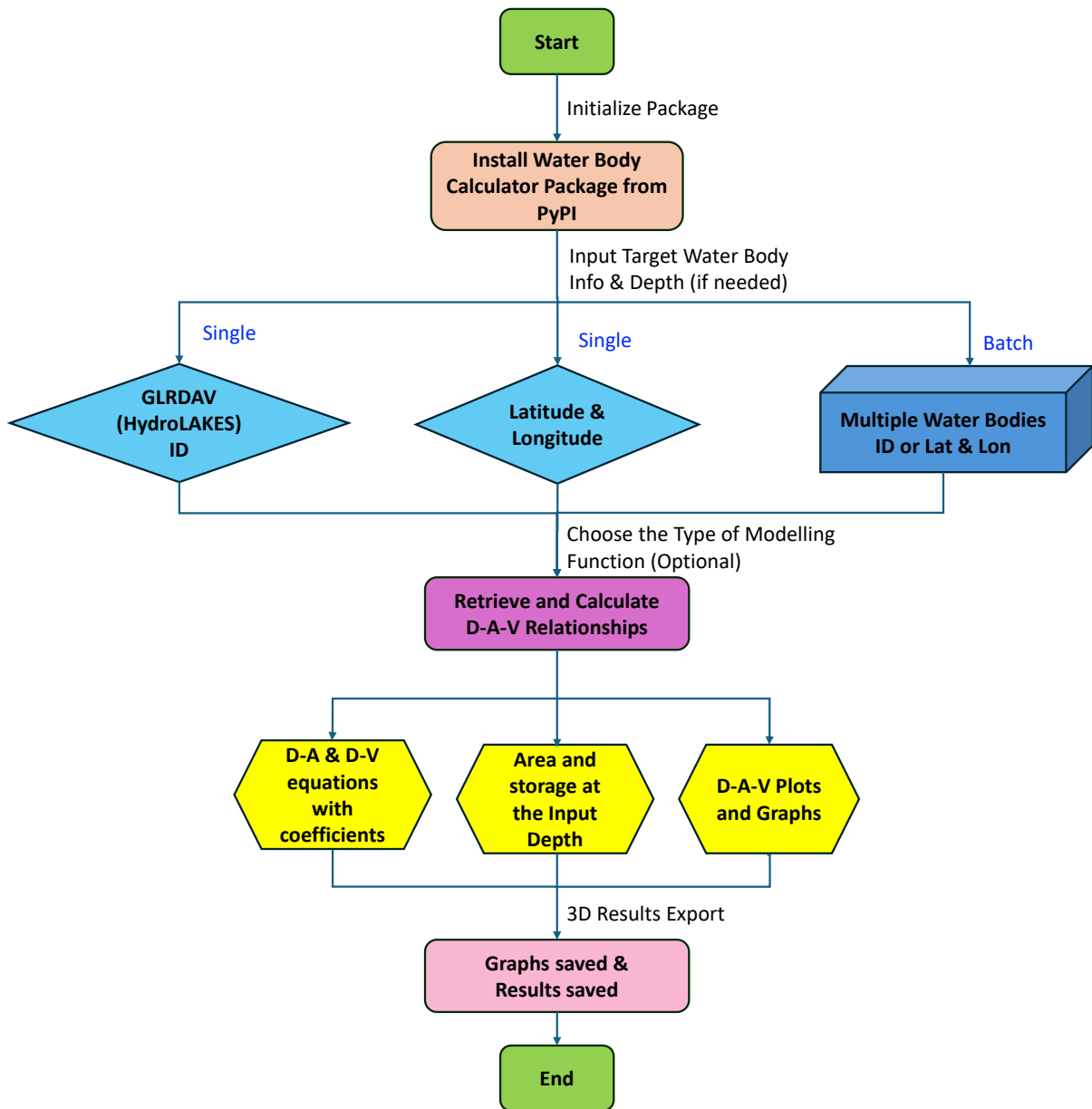


Figure 4.8. Workflow of the “Global Waterbody Calculator” Python package. Users can specify a single water body (by ID or geographic coordinates) or process multiple water bodies in batch mode. The tool retrieves the relevant D-A-V equations from GLRDAV, calculates area and volume at specified depths, and outputs both tabular and graphical results for further analysis.

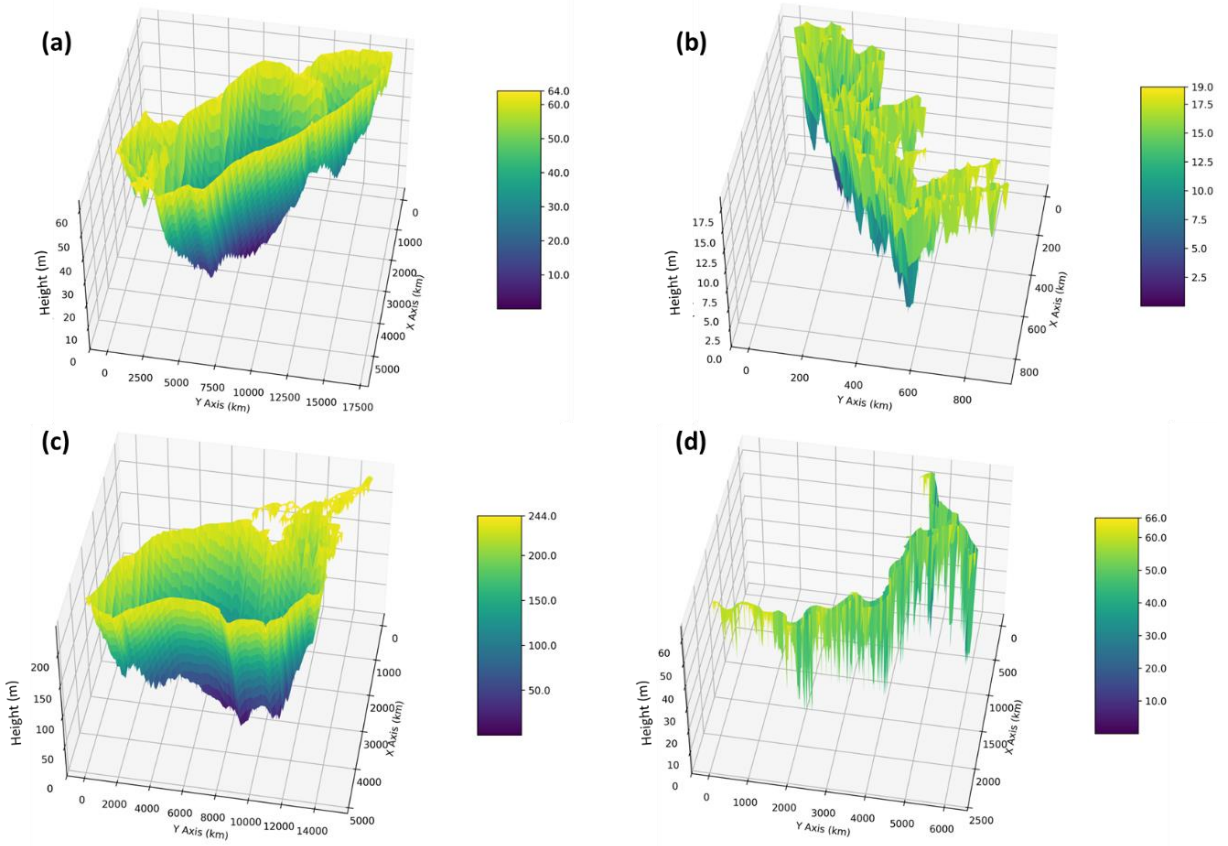


Figure 4.9. Three-dimensional bathymetry generated with the Global Waterbody Calculator from the GLRDAV D-A-V equations for four water bodies: (a) Lake Erie (maximum depth ≈ 66 m), (b) Cedar Creek Reservoir (maximum depth ≈ 19 m), (c) Lake Ontario (maximum depth ≈ 244 m), (d) Lake Diefenbaker (maximum depth ≈ 66 m).

4.5 Conclusion

The GLRDAV database addresses longstanding issues of the global waterbody D-A-V relationships, such as unit inconsistencies, oversimplified D-A-V equations, low spatial resolution, data errors, and cumbersome computational requirements. The GLRDAV database comprises over 17 million equations for over 1.4 million lakes and reservoirs with 0.1 m depth resolution, and 12 equations per waterbody (6 for depth–area and 6 for depth–volume relationships) presented as polynomial (orders 1–5) and power functions.

Against the ReGeom and GRDL datasets, 3rd–5th-order fits keep depth–volume RMSE near 0.20 km³ for ReGeom and ≈ 1.05 km³ for GRDL, about 10–20% lower than second-order or power-law forms while avoiding the negative predictions seen with first-order polynomials. Independent surveys from the Texas Water Development Board show the same equations more closely track measured bathymetry than either GRDL or ReGeom.

Importantly, our results underscore that more sophisticated and computationally demanding machine learning models, such as those employed in GRDL, do not necessarily guarantee a better performance. Instead, our approach—leveraging existing large-scale datasets and combining polynomial and power function formulations—is both computationally efficient and of wide practical applicability.

GLRDAV is distributed with an open-source Global Waterbody Calculator that converts any record to tabular or GeoTIFF bathymetry within seconds, enabling rapid coupling to hydrodynamic or biogeochemical models such as CE-QUAL-W2, EFDC, and Delft3D. Together, the database and toolset provide the first globally consistent, high-resolution morphometric foundation for continental-scale assessments of water storage, mixing, greenhouse-gas emissions, and climate-driven change.

Chapter 5

Phosphorus retention efficiency in dam reservoirs depends on outflow positioning and water level: Insights from Fanshawe Reservoir, Ontario, Canada

5.1 Summary

Dams represent potential water quality control points to reduce phosphorus (P) loads along the river continuum and, hence, help mitigate eutrophication in receiving water bodies. Here, we test how outflow routing and water level adjustment affect the phosphorus retention efficiency (PRE) of Fanshawe Reservoir. The reservoir is located on the Thames River, Ontario, Canada, within the Lake Erie watershed and receives high P loads from intensive livestock dominated agriculture upstream. We used the CE-QUAL-W2 model to simulate the thermal structure and water quality in the reservoir with a focus on P cycling processes, including the benthic recycling of dissolved reactive P (DRP) from the reservoir sediments (i.e., internal P loading). The model was calibrated and validated using a 2-year time series data set collected in 2018-2019. Next, we imposed a set of scenarios where the water level in the reservoir and the depth of water withdrawal at the dam were varied. Water release by the dam occurred either through the sluice gates (upper outflow), via deeper outlets (lower outflow), or both (normal operation outflow). The imposed water levels ranged by 10 m, from the normal operating water level to the maximum water level (+10 m). Key model outcomes include monthly water residence times (WRT) and the spatial distributions of temperature, dissolved oxygen (DO), total phosphorus concentrations (TP), and dissolved reactive phosphorus (DRP). Under normal dam operation, the average annual PRE of TP was 13% and exhibited large monthly variability. During summer-early fall, PRE reached its lowest values, even becoming negative with the reservoir becoming a net source of TP and DRP due to the combination of low inflowing P load and the development of a strongly stratified water column promoting internal P loading. Raising the water level to the maximum elevation and withdrawing water only via the upper outflow mitigated the downstream impacts of stratification-induced internal P loading, transforming the reservoir from a net source to a net sink of TP and DRP during summer. This adjustment increased summer PRE values to over 78% and the annual PRE of TP to above 50%. Thus, adaptive dam operation could be used to effectively reduce downstream riverine P loads, although potential trade-offs with other reservoir functions, such as recreational activities, hydroelectric production, and flow augmentation, would have to be considered alongside potential side effects, such as in-reservoir algal blooms and hypoxia.

5.2 Introduction

Human activities, including mining, sewage discharge, fertilizer application, and dam construction, have significantly altered the biogeochemical cycles of carbon and essential nutrients, including

phosphorus (P) and nitrogen (N) (Carpenter et al., 1998; Jarvie et al., 2006; Sharpley et al., 2013; W. Wang et al., 2021). Globally, human activities have led to P and N enrichment of freshwater and nearshore marine systems, causing many environmental management challenges, including the occurrence of harmful and nuisance algal blooms (L. Feng et al., 2024; Wells et al., 2020).

In freshwater systems, P is typically the dominant limiting macronutrient. Therefore, increases in riverine P loads can cause eutrophication in receiving water bodies (Carpenter, 2008; Schindler, 1977; Schindler et al., 2008). Biogeochemical processes in dam reservoirs, however, can significantly alter the fluxes and speciation of P along river networks (Maavara et al., 2015; Van Cappellen & Maavara, 2016). While the impact of dam construction on the global P cycle is now well recognized, the variability of P retention efficiencies in reservoirs and their implications in, and downstream of, reservoirs remain inadequately understood (Maavara, Chen, et al., 2020). This uncertainty is compounded by the complex set of environmental drivers that control the fate and transport of P in reservoirs, making nutrient management along the river continuum a challenging task (Jarvie et al., 2012, 2017; Maavara et al., 2015; Powers et al., 2016; Sharpley et al., 2013).

Previous studies have analyzed the impact of changes in water level on nutrient dynamics in reservoirs (He et al., 2022, 2023), as well as the effects of selective water withdrawal strategies on in-reservoir thermal stratification and algal productivity (Carr et al., 2020; Lindenschmidt et al., 2019; Song et al., 2023; H. Wang et al., 2024). These studies highlight the close interplay between operational dam management and ecological outcomes, such as the in-reservoir water temperature regime (He et al., 2022). Here, we focus on the potential of dam operation to enhance the retention of P by reservoirs. This is especially important for watersheds where reservoir management could complement other best management practices in achieving P load reductions to sensitive downstream ecosystems impacted by eutrophication.

For our case study, we selected Fanshawe Reservoir in Ontario, Canada, because of the availability of a detailed 2-year long data set on weather conditions, stream flow and water quality (Kao et al., 2022). The data show that, while on an annual basis the reservoir is a net sink of total P (TP), it becomes a source of dissolved reactive P (DRP) when the water column stratifies during the warmer months. During stratification, hypoxia promotes the release of dissolved P from the bottom sediments to the deeper waters of the reservoir (Orihel et al., 2017). As noted by Kao et al. (2022), the

downstream transfer of P released during stratification is facilitated because the P enriched water is withdrawn via the bottom outflow gates of the dam.

Fanshawe Reservoir is the largest dam reservoir along the Thames River. The river runs through a fertile fluvial valley and receives high loads of P from intensive agriculture and urban sources before discharging into Lake St. Clair, which in turn flows into the Western Basin of Lake Erie (Bocaniov et al., 2019; Mohamed et al., 2019). To counter the increasingly frequent and severe harmful algal blooms in Lake Erie's western basin, Canada and the United States have agreed to further reduce P inputs from the tributary watersheds (Mohamed et al., 2019), including a 40% reduction in TP loading from the Thames watershed as part of the Canada-Ontario Action Plan (Environment and Climate Change Canada & Ontario Ministry of the Environment and Climate Change, 2018).

Here, we explore whether tuning the operational management of Fanshawe Reservoir could contribute to such a TP load reduction. We focus on the effects of altering the water level in the reservoir and the depth from which water is withdrawn through the dam. We hypothesize that controlling the positioning of the dam outflow and the reservoir water level could provide simple levers to modulate the P retention efficiency (PRE) of Fanshawe Reservoir, because of their effects on key variables including the water residence time (WRT) and the in-reservoir distributions of water temperature, dissolved oxygen (DO), TP, and DRP.

To test this hypothesis, we combined a 2-year time series dataset of flow and water quality data for Fanshawe Reservoir with the CE-QUAL-W2 model. The latter has been widely applied to investigate water quality issues in reservoirs (J. Bai et al., 2022; Cole & Wells, 2017; Lindenschmidt et al., 2019). After calibrating and validating the model, the effects of varying the reservoir water level and the routing of water withdrawal at the dam were simulated. A specific aim was to determine whether it would, in principle, be possible to overcome the poor PRE performance observed during the period of summer stratification. In addition to the direct implications for Fanshawe Reservoir, the process-based modeling results also yield transferable knowledge that may guide the inclusion of dam operational practices in watershed-scale nutrient management strategies. This is particularly relevant given the continued worldwide construction of new dams and the growing concerns about the ecological, economic, and health impacts of eutrophication (Dodds et al., 2009; Ho et al., 2019; Hou et al., 2022).

5.3 Methods and materials

5.3.1 Fanshawe Reservoir

The Thames River watershed is situated in one of the most intensive agricultural areas of southwestern Ontario (Quinlan, 2013) and constitutes the single largest source of P to the western basin of Lake Erie from the Canadian site, via Lake St. Clair (Maccoux et al., 2016). Fanshawe Dam is located on the North Thames River, just upstream of the confluence with the Southern Thames River in the City of London (Figure 5.1a). The North Thames River supplies the bulk of the external TP loading (95%) to the reservoir, with a much smaller (5%) contribution from the tributary Wye Creek (Figure 5.1b) (Kao et al., 2022). Hydrological information on Fanshawe Reservoir can be found in the Table 5.1. Between 1954 and 2004, the water residence time (WRT) ranged from 5 to 20 days with an average of 9.5 days. Water withdrawal from the reservoir occurs via two sets of outlets: surface sluice gates and two adjacent bottom draw valves. One bottom draw valve is used for hydroelectric power generation and the other functions as a low-flow valve. Water quality assessments reveal eutrophic to hypereutrophic conditions in the reservoir, characterized by harmful algal blooms and oxygen depletion, particularly during periods of thermal stratification in the summer (Nürnberg, 2007).

5.3.2 Water quality model

The CE-QUAL-W2 model is an open-source finite difference, two-dimensional (2-D), laterally averaged hydrodynamic and water quality simulation tool co-developed by the US Army Engineer Waterways Experiment Station and Portland State University (Cole & Wells, 2017). The model is especially well-suited for simulating the coupled flow, temperature, and water quality dynamics in multi-branched river reservoirs under imposed streamflow and meteorological forcing. Water quality computations account for the major ecosystem (e.g., primary production, grazing), biogeochemical (e.g., organic matter mineralization, benthic nutrient recycling), and physical-chemical (e.g., sorption, particulate matter settling) processes that regulate the interactions between nutrients, phytoplankton and water column oxygenation. As a result, the model can generate a broad range of outputs including the spatial-temporal distributions of water temperature, dissolved oxygen, and nutrients such as P.

Here, we used CE-QUAL-W2 version 4.1, focusing on the seasonal variations of in-reservoir P cycling and the resulting PREs of TP and DRP. The capability of CE-QUAL-W2 to integrate water

column and benthic biogeochemical P cycling was crucial for simulating the variable contributions of external and internal P loading to the reservoir's water column. Net production of pore water DRP in the sediment was modeled as a first-order decay of the particulate organic P. However, as commonly observed in lentic systems (Markelov et al., 2019; Orihel et al., 2017), the efflux of pore sediment DRP to the water column was assumed to occur only when the DO of the bottom water dropped below the hypoxic threshold value of 2 mg/l. All the kinetic expressions in the P cycling calculations were the default formulations described in the CE-QUAL-W2 manual version 4.1 (Cole & Wells, 2017). Two years of stream inflow, dam outflow, meteorological, and water quality data (2018-2019) were employed in the development of the CE-QUAL-W2 model for Fanshawe Reservoir. The data from the first year (2018) were used to calibrate the model, while those from the second year (2019) were used to validate its predictive capabilities under different hydrometeorological conditions. For the complete description of the data acquisition protocols, the reader is referred to Kao et al. (2022).

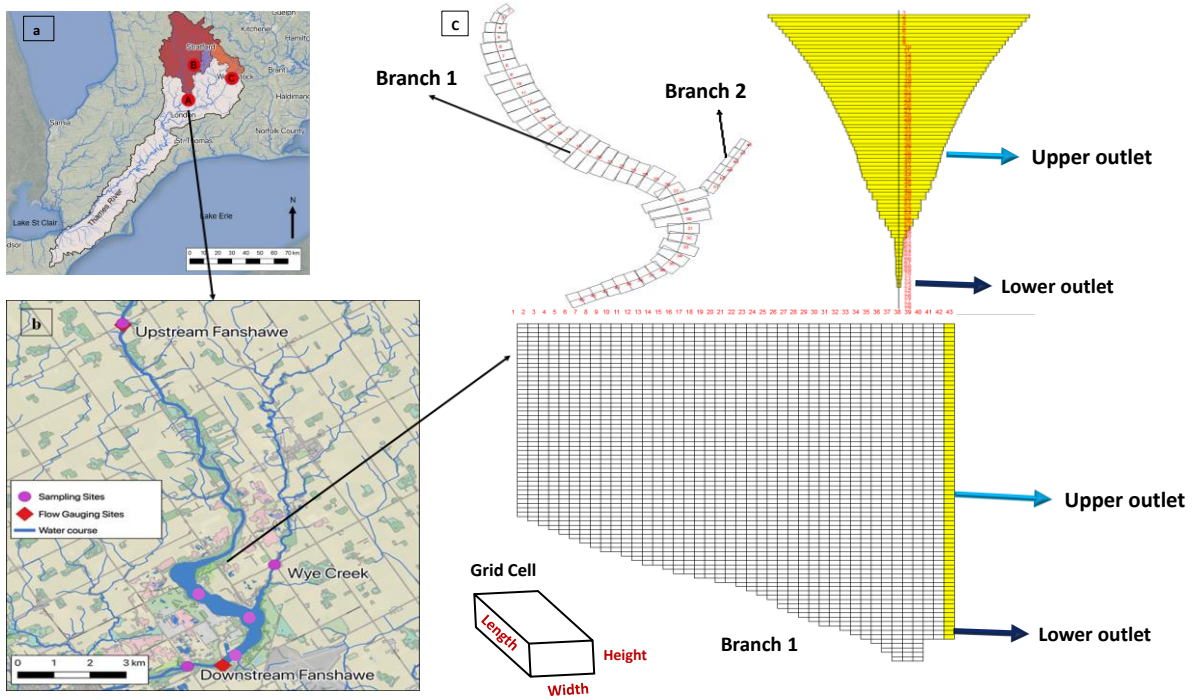


Figure 5.1: Overview map of (a) the Thames River Watershed and (b) Fanshawe Reservoir.

In panel a, A is Fanshawe Reservoir, B is Wildwood Reservoir, and C is Pittock Reservoir. In panel b, red diamonds are Water Survey of Canada flow gauging stations, purple circles are the water sampling locations (Yu, 2020 and Kao, 2021). Panel c illustrates the grid model domain:

top view shows the main branch of the reservoir and the Wye Creek tributary (Branch 2), end view at the dam shows the depths of the outlets, and side view shows the bottom topography (the yellow grid cells are those adjacent to the dam). Segment numbering identifies the longitudinal location of grid cells, with segment 1 being the most upstream location closest to the inflow point of the North Thames River and segment 43 being adjacent to the dam. Layer numbering indicates the depth of the grid cells, with layer 1 corresponding to the topmost elevation. The dam upper and lower outlet positions are at layer 39 and 72, respectively. Each grid cell has a length of 150 meters, a height of 0.3 meters but with variable width depending on the layer number (i.e., depth).

Table 5.1. Hydrological data for Fanshawe Reservoir from Nürnberg and Lazerte (2005).

Parameter	Values
Altitude of average pool level (m above sea level)	262.4
Watershed area (km ²)	1447.4
Surface area (km ²)	2.726
Maximum depth (m)	12.1
Mean depth (m)	4.82
Volume (m ³)	13.146 x 10 ⁶
Outflow volume (m ³ per year)	560 x 10 ⁶
Water Residence Time (days)	9.5

5.3.3 Input data, model domain, and model scenarios

Details on the input data used in model development, calibration and validation can be found in Appendix D. The gridded discretization of the reservoir (Figure 5.1) was based on available topographic and bathymetric information (Yu, 2020). Daily water inflow data and climatic variables for the years 2018 and 2019, including air temperature, wind speed, wind direction, and cloud cover, were sourced from the London airport station of Environment and Climate Change Canada (ECCC). Approximately half (49.9%) of the reported wind speed ranged between 0 and 4 m/s, and only a small fraction (7.3%) exceeded 8 m/s. Cloud cover data were scaled from 0 (clear) to 10 (full cloud cover).

Data on water level and dam outflow were obtained from the Upper Thames River Conservation Authority who operate the dam (UTRCA; personal communication, 2023).

Water quality data included TP and DRP concentrations from the main (North Thames River) and secondary branch (Wye Creek) discharging into the reservoir, as well as from a location just downstream from the dam. These data, plus water temperature and in-reservoir water quality data, have been presented by Kao et al. (2022). Additionally, data from three sediment cores collected from the reservoir on July 9, 2018, were used to parameterize the sediment diagenesis sub-model. Specifically, we estimated the average sediment organic P concentration (150 mg/kg) based on measured TP concentrations. This concentration was then combined with a first-order rate constant to represent the mineralization of sediment organic P into pore water DRP (Appendix D).

An existing grid model of Fanshawe Reservoir (Yu, 2020) was expanded from its original 39 horizontal segments and 19 vertical layers to 52 segments and 79 layers to accommodate the variable volume, WRT, and outflow scenarios (see next section). The implemented grid model is illustrated in Figure 5.1. Note that the inflow from the North Thames River into the reservoir is imposed at the upper boundary (segment 1), while the inflow from Wye Creek enters via segment 28. Changes in the water level of the reservoir therefore translate into a variable number of depth layers over which the inflow was evenly distributed in segments 1 and 28.

A total of 33 scenarios were considered to evaluate the impacts of different combinations of outflow and water level conditions on key water quality variables and the retention efficiency of total P. The three primary outflow scenarios were (Figure 5.1c and Appendix D): (1) “Normal Outflow”, which corresponds to the dam’s standard outflow operation in which most outflow occurs via the bottom draw valves, except when high inflow volumes resulting from heavy rainfall events or snowmelt occur and the sluice gates are also used, (2) “Top Outflow” where all water is released at an elevation of 262 m through the dam’s sluice gates, and (3) “Bottom Outflow” where all water is exclusively discharged through the dam’s lower outlet valves at 252 m elevation.

The dam discharge data imposed in the Normal Outflow scenario during the years 2018 and 2019 are shown in Figure D.5 in Appendix D. For each of the primary outflow scenarios, 11 different water levels were tested, starting from the standard operational baseline water level (i.e., at 262 m elevation) and extending 10 meters upwards, with results provided for each one-meter increment. The highest water level tested (baseline + 10 m) corresponds to the top of the dam (i.e., at 272 m elevation) and

therefore represents the theoretical maximum water level that can be realized (Appendix D, Figure D.2).

5.3.4 Phosphorus retention and enrichment

Dam reservoirs generally retain a fraction of the TP supplied by river inflow and atmospheric deposition (Maavara et al., 2015). In that case, $TP_{in} > TP_{out}$ where TP_{in} and TP_{out} are the TP input flux to, and output flux from, the reservoir, respectively. The TP retention efficiency, or PRE, can then be calculated as a percentage of the TP input to the reservoir as:

$$PRE = \left(\frac{TP_{in} - TP_{out}}{TP_{in}} \right) \times 100 \quad \text{when } TP_{in} \geq TP_{out} \quad \text{Equation 5-1}$$

Equation 5-1 then gives PRE values ranging between 0 (no retention) to 100% (complete retention). In some instances, however, more TP may be leaving than entering the reservoir (i.e., $TP_{out} > TP_{in}$), for example, during periods of low river inflow and intense internal P loading from the benthic sediments. When the reservoir acts as a source of TP to the dam outflow (enrichment), we used:

$$PRE = - \left(\frac{TP_{out} - TP_{in}}{TP_{out}} \right) \times 100 \quad \text{when } TP_{out} \geq TP_{in} \quad \text{Equation 5-2}$$

Henceforth, negative PRE values will indicate a higher TP loading flowing out of the dam than entering the reservoir. In the extreme case where all the outflow TP is generated within the reservoir, Equation 5-1 would yield $PRE = -100\%$. Thus, for both TP retention and enrichment by reservoirs the absolute values of PRE scale between 0 and 100%. Further justification for Equation 5-1 and Equation 5-2 can be found in Zhou et al. (2024) and Appendix D.

5.3.5 Model performance and statistical analyses

Model performance was assessed by computing the Mean Error (ME), the Mean Absolute Error (MAE), and the Root Mean Square Error (RMSE) according to:

$$ME = \frac{\sum_{i=1}^n (X_{iobs} - X_{imod})}{n} \quad \text{Equation 5-3}$$

$$MAE = \frac{\sum_{i=1}^n |X_{iobs} - X_{imod}|}{n} \quad \text{Equation 5-4}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (X_{iobs} - X_{imod})^2}{n}} \quad \text{Equation 5-5}$$

where n is the number of data points, X_{iobs} is the observed data point, and X_{imod} is the corresponding modeling result. Values of ME, MAE, and RMSE approaching 0 indicate increasingly good agreement between model-predicted and observed results. Linear correlations between parameters were assessed with the linear correlation coefficient (R), which ranges from -1 to +1, where +1 indicates a perfect positive correlation, -1 indicates a perfect negative correlation, and 0 signifies no correlation. Regression coefficients and intercepts were computed using Python's scikit-learn library. Correlations were considered statistically significant for p -values below 0.01; the t -distribution was assumed when calculating 95% confidence intervals (Bruce et al., 2020).

5.4 Results

5.4.1 Hydrodynamic and P processes

5.4.1.1 Water column mixing, temperature and oxygenation

The model satisfactorily reproduces the observed reservoir's dynamic variations in water level (Figure 5.2a, Appendix D, Table D.3; ME = 0.002m, MAE = 0.04m, RMSE = 0.08 m), as well as those of the water temperature depth profiles (Figure 5.2b, $n = 54$, RMSE = 1.83°C) and the surface water temperature (Figure 5.2c, $n=37$, RMSE = 1.28°C,). Appendix D provides further comparisons of measured and modelled temperature profiles. Overall, both seasonal trends and short-term fluctuations are captured by the model, demonstrating its ability to simulate the physical processes driving stratification, mixing, DO and nutrient P cycling in the reservoir.

The model predicts slight vertical stratification of the dissolved oxygen (DO) concentrations during the winters of 2018 and 2019, with systematically higher DO levels in the upper layers. This stratification dissipates in spring as increased inflow and higher mixing intensity, combined with enhanced photosynthesis, oxygenating the water column (Figure 5.3a). The DO concentrations in

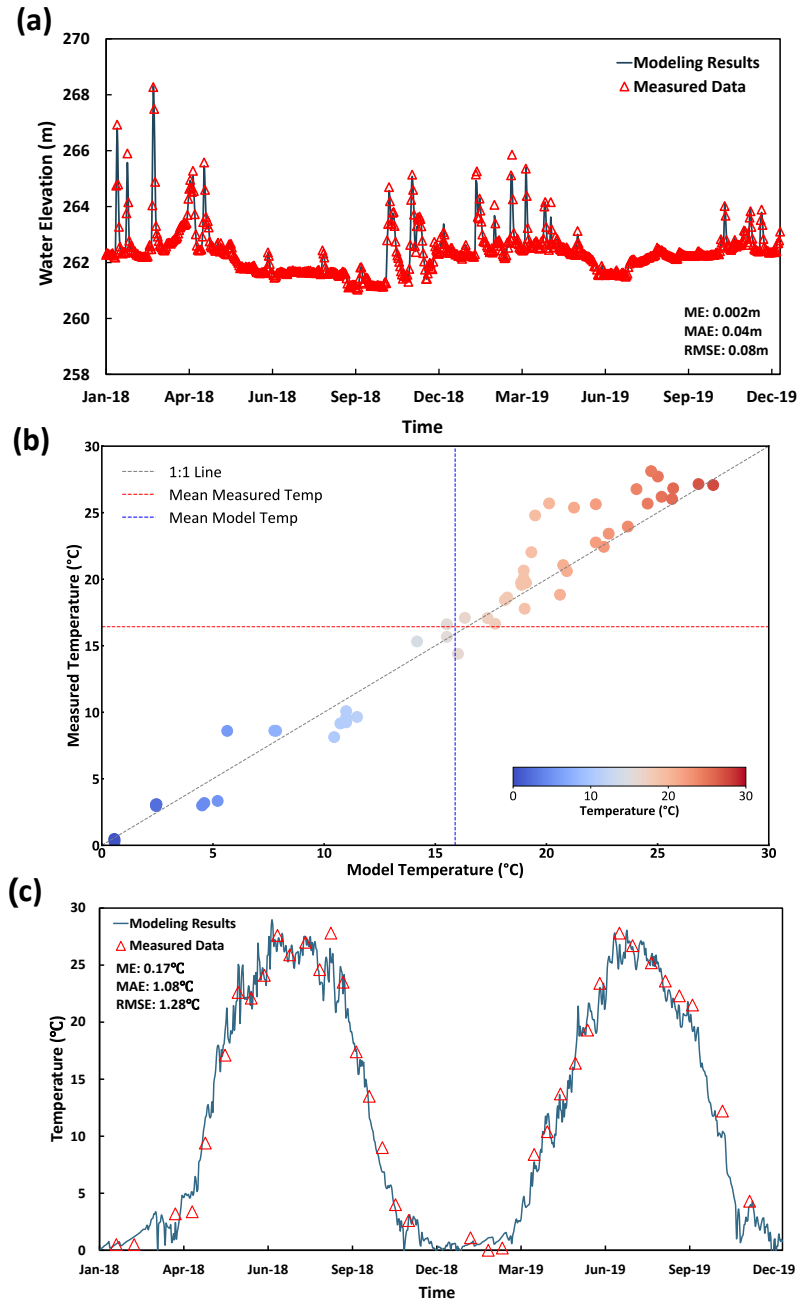


Figure 5.2. Comparison of model simulation results with measured data in Fanshawe Reservoir from 2018 to 2019. (a) Simulated vs. observed water levels, (b) simulated vs. observed depth-distributed water temperature profiles, with 1:1 line, (c) simulated vs. observed surface water temperatures.

spring exhibit sharp fluctuations particularly in the bottom layers, reflecting the dynamic interaction between highly variable inflows and in-reservoir processes (Appendix D, Figure D.4).

During the summer in both years, a pronounced thermocline develops at around 5 m water depth leading to significant oxygen depletion in the hypolimnion while concentrations at the surface remain high. According to the model results, DO levels in the hypolimnion dropped below 2 mg/l for a total of 48 days between January 2018 and December 2019, highlighting the important role of thermal stratification in limiting oxygen availability in the deeper layers. In autumn, cooler air temperatures and increased wind-induced mixing disrupt the stratification, restoring a more uniform vertical DO profile.

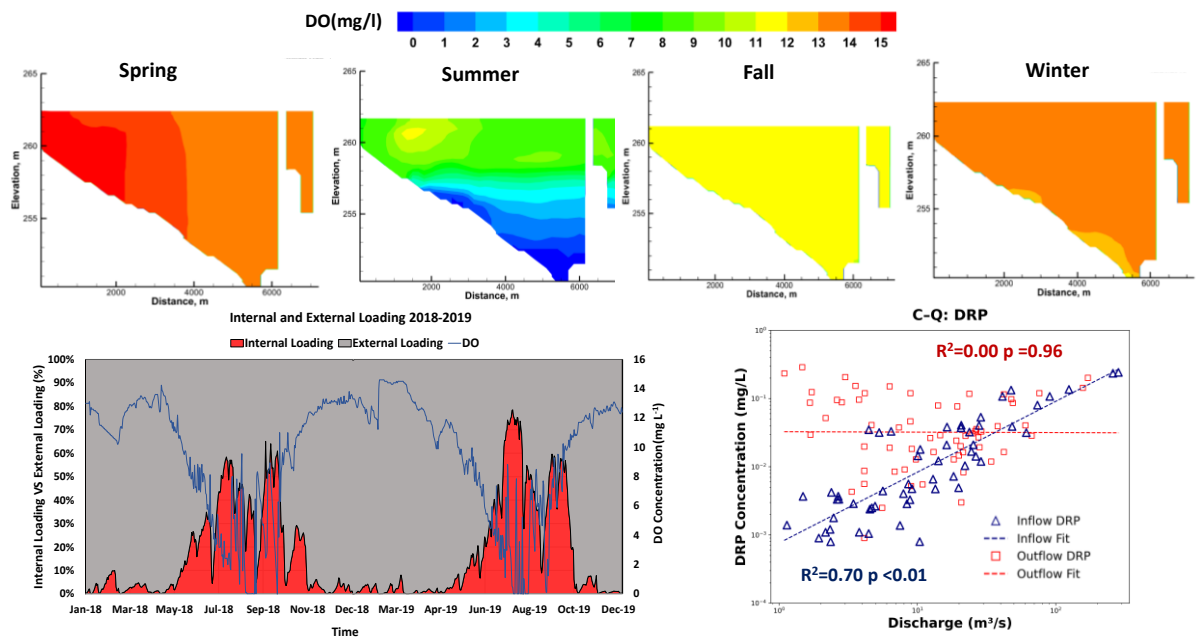


Figure 5.3. Upper panels: model-simulated seasonal distributions of DO in Fanshawe Reservoir. Lower left panel: model-simulated contributions of internal TP loading (red area) and external TP loading (grey area), together with the bottom DO concentrations (blue lines) from 2018 to 2019. Lower right panel: Concentration - Discharge Relationships (C-Q) for DRP comparing inflow (blue) versus outflow (red). Note the change from a positive slope (enrichment) of the inflow C-Q to a near-zero slope (chemostatic) for the outflow C-Q.

5.4.1.2 P concentrations and loads

Phosphorus, as a primary limiting nutrient in freshwater ecosystems, is closely related to primary production and aquatic biomass. Our study quantitatively investigated the seasonal variations of TP, including the role of sediment recycling or internal P loading. The strong seasonal variations in the relative contributions of internal (sediment-derived) and external (inflow-derived) loading shown in Figure 5.3 clearly correlate with the variations in bottom-water DO concentration. During late winter and early spring, external loading predominated (> 90% of the total TP loading to the water column) while bottom DO remained above 8 mg/l. As stratification intensified in summer, the hypolimnion became anoxic, driving a surge in sediment DRP release that, on certain days, exceeded 70–80% of total TP loading. Minor year-to-year differences between 2018 and 2019 reflected inter-annual differences in hydrometeorological drivers; for instance, warmer, lower-flow conditions in August 2019 yielded more prolonged hypoxia and higher internal P peaks than in 2018. Averaged over the two years, the model-predicted annual retention efficiency (PRE) of Fanshawe Reservoir was 13% of the TP inflow.

During periods of high internal P loading, particularly in summer and early fall, the reservoir can act as a source of P, hence, increasing the outflow TP load relative to the inflow TP load. By contrast, during the high-flow spring seasons, the reservoir acts as a sink, retaining P supplied from the upstream catchment. During this period, internal P loading has a minimal impact on the water column's TP budget (Figure 5.3). The model results also revealed significant seasonal variations in sediment DRP fluxes. The annually averaged benthic effluxes amounted to 8.7 mg P/m²/d, while the corresponding July–August effluxes ranged from 10 to 32 mg P/m²/d, with an average of 20 mg P/m²/d. These results highlight the alternating role of the reservoir as a source and a sink for phosphorus, depending on seasonal variations in the hydrodynamic and climate drivers.

The comparison between measured and modelled DRP and TP concentrations in the reservoir (Figure 5.4a) showed that the model provided a reasonable representation of the temporal and vertical concentration trends. However, both model derived DRP and TP concentrations tended to be underestimated compared to measured values. For example, the mean simulated surface-layer DRP concentration on measured days was 0.015 mg/l, whereas the observed mean was 0.024 mg/l (RMSE = 0.03 mg/l; MAE = 0.01 mg/l). Model performance was comparable between years: in the calibration year 2018, the RMSE value for surface DRP was 0.030 mg/l, while in the independent validation year 2019, the corresponding RMSE was the same, 0.030 mg/l. Full performance metrics

for 2018 (Table D.3a), 2019 (Table D.3b), and the combined dataset (Table D.3c) are provided in the Appendix D.

Nonetheless, close agreement, without a systematic bias, was found between measured and modelled loads of DRP and TP downstream of the dam (Figure 5.4b), supporting the use of the model to estimate PRE values. However, four outlier days (Julian Days 331, 369, 401, 439) were identified during which the measured DRP concentrations were considerably higher than predicted by the model. These days all coincided with exceptionally large and abrupt changes in inflow rates—each showing an increase of over 200 m³/s compared to the previous day (Figure D.5). Including these outliers, the model predicted mean daily downstream loads of DRP and TP of 144.6 kg/day and 259.2 kg/day, respectively, with corresponding RMSEs of 140.6 kg/day and 237.1 kg/day (and MAEs of 54.6 kg/day and 109.1 kg/day, Appendix D, Table D.3c). When the previously mentioned outliers were excluded, model performance improved dramatically. While the model does not capture short-term perturbations of the reservoir's water balance (i.e., much shorter than the average WRT), these perturbations are unlikely to have a major effect on the reservoir's long-term (≥ 1 month) P budget.

Further insights into the P export dynamics were provided by comparing the log–log concentration–discharge (C–Q) relationships of DRP and TP at both the inflow and outflow (Figure 5.3c and Figure D.10). For DRP, the observed C–Q relationship (with C in units of mg/l and Q in units of m³/s) was $\log C = -3.12 + 1.04 \times \log Q$ ($R^2 = 0.70$, $p < 10^{-15}$) indicating a runoff mobilization behavior. At the outflow, however, the slope between C and Q was essentially zero: $\log C = -1.49 - 0.0065 \times \log Q$ ($R^2 \approx 0$, $p = 0.96$), or $C \propto Q^{-0.0065} \approx \text{constant}$. The latter corresponds to chemostatic behavior where the DRP concentration is independent of the flow rate.

A similar tendency toward chemostatic behavior was observed for TP. At the inflow, the C–Q relationship was $\log C = -1.69 + 0.45 \times \log Q$ ($R^2 = 0.38$, $p = 4.8 \times 10^{-7}$), whereas the downstream C–Q relationship showed a much weaker dependence on Q: $\log C = -0.93 - 0.09 \times \log Q$ ($R^2 = 0.025$, $p = 0.25$). The CE-QUAL-W2 model reproduced the observed differences in C–Q slopes between inflow and outflow for both TP and DRP. Thus, the changes in C–Q relationships between inflow and outflow could therefore be attributed to in-reservoir processes (e.g., photosynthetic P fixation, stratification-induced internal P loading) that decouple the TP and DRP concentrations from the river discharge dynamics.

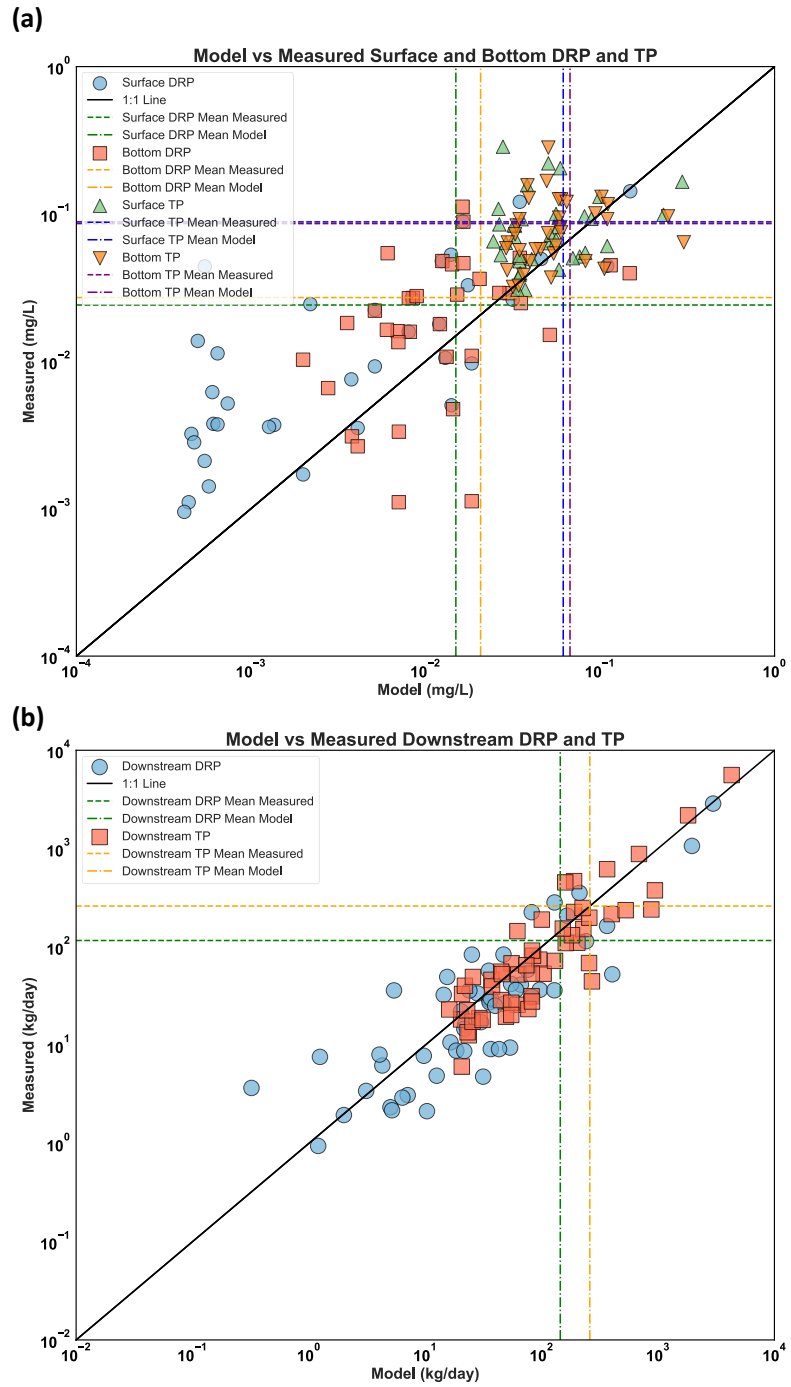


Figure 5.4. Modeled versus measured (a) in-reservoir DRP and TP concentrations (in mg/l) and (b) DRP and TP loads downstream of the dam (in kg/day). Note that the graphs are on a log-log scale with 1:1 line.

5.4.2 Model scenarios

5.4.2.1 Water level and outflow effects on PRE

The 33 simulation scenarios where the reservoir water level was incrementally raised up to +10 m above the normal operating level illustrate how water level control (WLC) and outflow depth together shape the retention efficiency of TP (PRE). The boxplots in Figure 5.5a show the monthly averaged PRE values for the Normal, Top, and Bottom outflow conditions and across all the water levels combined, whereas the shading intensity of the symbols on the violin plots of Figure 5.5b identifies the various water levels.

During the February–April period, elevating the water level resulted in moderate increases in PRE, but the outflow position (i.e., Top, Bottom, or Normal) had little impact. For example, in February, the mean PRE values clustered around 38% (Normal: 36.9%, Top: 38.8%, Bottom: 38.3%). These minimal differences were due to the efficient water column mixing that maintained uniform depth P distributions. That is, hydrometeorological drivers (i.e., inflow rates, WRT, cool temperatures) control net P sequestration in late winter–early spring, rendering the reservoir a stable P sink regardless of the outflow positioning.

Starting in late spring, with inflow dropping and thermal stratification intensifying, the outflow depth exerted a more pronounced influence on P retention. Under Top outflow, the reservoir remained mostly a net TP sink, peaking at 78% PRE in July at +9 m WLC. By contrast, Normal outflow at +9 m WLC yielded only 24% retention that same month. This discrepancy underscores how directing the outflow via the surface gate sluices effectively isolated the P-enriched bottom waters from leaving the reservoir, boosting P retention. Taking all scenarios together, the reservoir shifted more readily to net TP export in July or August, once hypolimnetic hypoxia and internal P loading reached their seasonal maximum.

During fall, the reservoir partially reverted to higher-flow conditions reminiscent of early spring, narrowing the differences between the outflow scenarios. By November, the reservoir again acted as a P sink. Unlike in spring, however, the reservoir for the most part remained a net P source in September–October (Figure 5.5a). The model results indicated that prolonged warm surface temperatures (around 20°C), persistently low hypolimnetic DO, and reduced inflow rates in September favored the continued internal P loading to the water column. Bottom water DO only rose substantially after late October, when stronger mixing eventually restored net P retention.

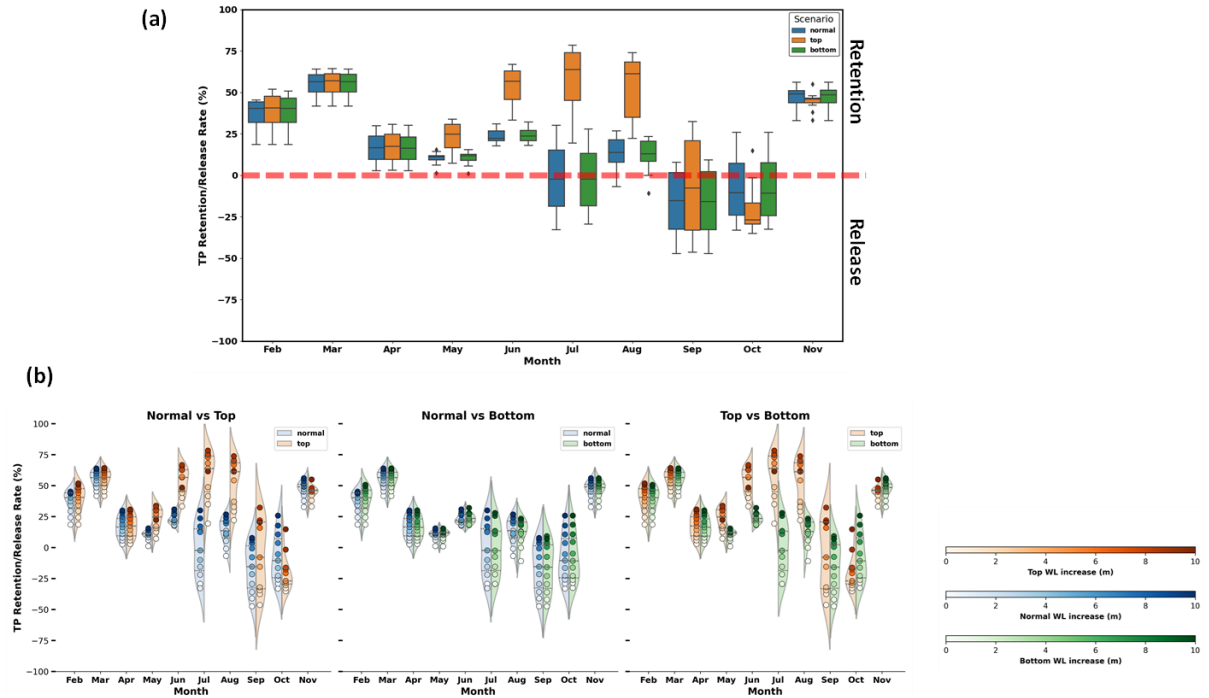


Figure 5.5. Boxplot of monthly PRE for Normal (blue), Top (orange), and Bottom (green) outflow positioning. In (a), for each of the outflow positioning, the boxplots combine all 11 imposed water levels (from 0 to +10 m); in (b) the shading intensity of the symbols is used to explicitly indicate the water level. Note that in (b) the comparative plots between Normal and Bottom show little difference because, under Normal conditions, most outflow occurs via the lower (bottom) gates.

5.4.2.2 PRE and underlying mechanisms

Considering the results from the 33 scenarios that combined 11 water levels (0 to +10 m) and 3 outflow positionings (Normal, Top, Bottom), the average annual PRE increased from 13% under baseline water level (0 m) plus Bottom withdrawal up to 52% under the maximum water level (+10 m) with Top withdrawal (Table D.5). The latter 52% was the outcome of both the increased water level and the Top outflow. For example, for the baseline water level condition (0 m), switching from Normal to Top outflow raised the average annual PRE from 13% to 20%. Even modest water level increases, for example +2 m, combined with Top withdrawal raised the annual PRE to 29%. In comparison, in the +2 m plus Normal outflow scenario, the annual PRE value was only 18%. Thus, using the Top outflow elevation alone can substantially enhance P retention, even when practical reasons prevent the water level from being increased.

Higher water levels prolong the reservoir's water residence time (WRT), which is a key driver of PRE. Under Top outflow, September WRT rose from 35 days at 0 m water level to 149 days at +10 m (Figure 5.6), allowing more processing of the incoming river-borne P. Although extending the WRT causes more build-up of hypolimnetic DRP, the Top outflow releases DRP-depleted surface water while the P-rich deep water is trapped below the thermocline. In spring (February–April), high inflow rates and thorough mixing yielded stable PRE irrespective of outflow position. During summer stratification (May–September), hypolimnetic anoxia driven sediment-derived DRP efflux, elevating bottom-water TP by up to 573% under +4 m water level plus Top withdrawal. However, because the P-enriched hypolimnion remains in the reservoir, the July PRE for the + 9 m water level reached 78%. By contrast, Normal and Bottom outflow scenarios allow for the internal P loading to be exported from the reservoir causing PRE to become negative.

As shown in Figure 5.6, varying water level and outflow depth modulate reservoir stratification and oxygen distributions. Top withdrawal enhances vertical temperature gradients (up to 7.2°C difference between top and bottom layers in August at +10 m) and delays the onset of bottom water DO dropping below 2 mg/l by around 30 days. Under these conditions, a metalimnetic oxygen minimum (MOM) appears that buffers against internal P loading (Figure D.8). Bottom withdrawal reduces MOM buffering and, therefore, reduces PRE. Overall, the PRE trajectories diverge most sharply during the peak stratification months because surface water withdrawal through the dam maximizes retention, whereas bottom withdrawal can lead to net P export. After the fall overturn, the scenarios converge again. Together, these findings underscore that the seasonally targeted use of surface-gate withdrawal could effectively enhance annual PRE and thus contribute to the proposed reduction of P inputs to the downstream Lake Erie-Lake St. Clair system. However, the implementation of such a mitigation strategy would have to consider the potential trade-offs with extended in-reservoir hypoxia that may affect water quality and reservoir functions.

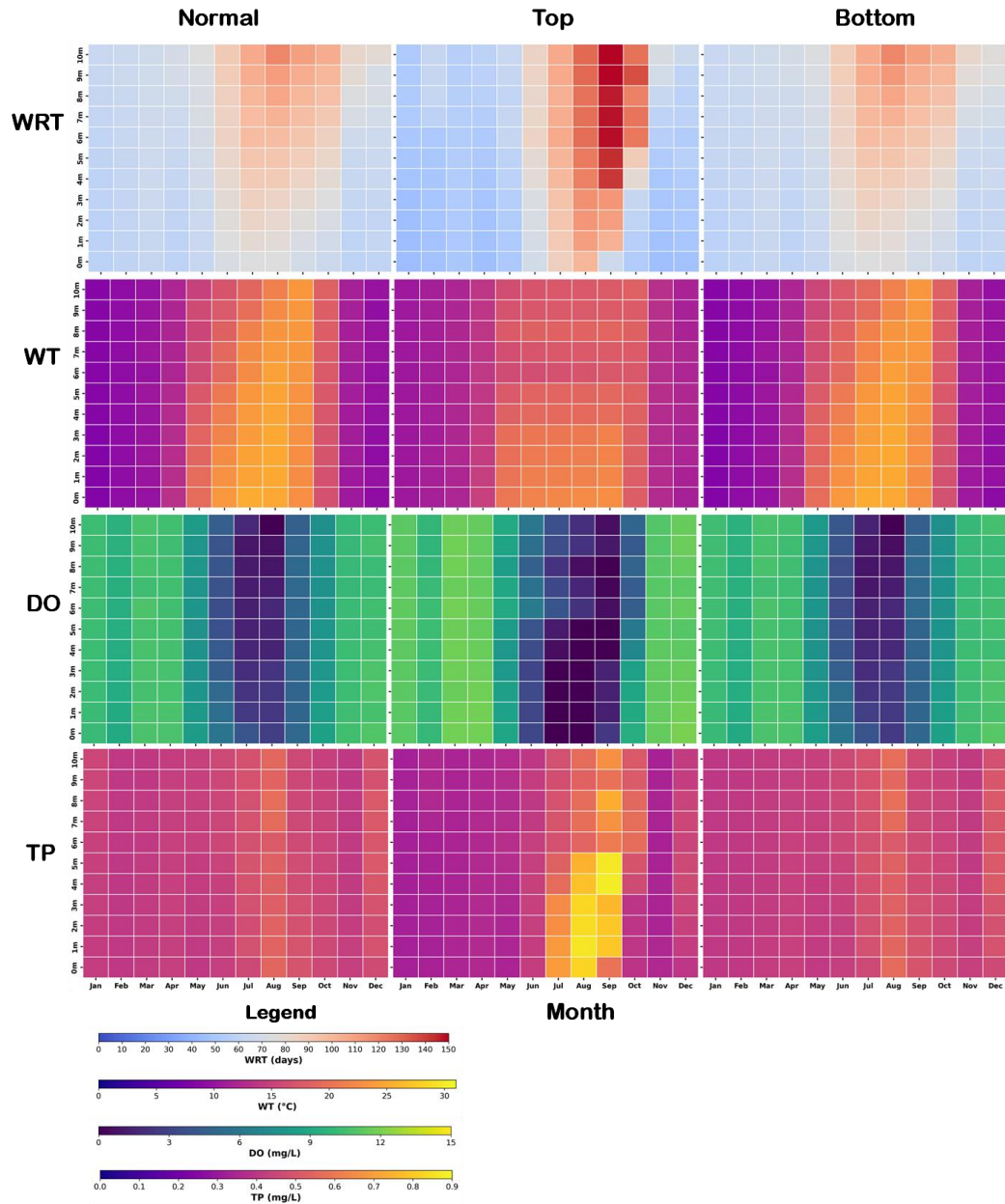


Figure 5.6. Monthly averaged bottom water residence time (WRT), water temperature (WT), and dissolved (DO) and total phosphorus (TP) concentrations for the 33 different scenarios at the deepest cell before the dam. (1) Outflow positioning: Normal: standard dam operation outflow; Top: all discharge from upper outflow gates; Bottom: all discharge from lower outflow gates. (2) Water level scenarios are indicated on the vertical axis, with 0 m corresponding to the 2018 baseline water level and +10 m representing the maximum water level.

5.5 Discussion

5.5.1 Managing phosphorus retention in stratified reservoirs

Relatively few studies have examined the combined effects of adaptive water level management and outflow positioning to address nutrient enrichment issues (Lindenschmidt et al., 2019; Song et al., 2023). Our modeling of Fanshawe Reservoir shows that raising the reservoir's water level during summer and drawing water from the upper gates can substantially increase P retention and, therefore, lower downstream P river loads. Under the most extreme tested scenario (+10 m water level), annual PRE could be increased from 13% under normal dam operation to over 50%, underscoring the potential for adaptive dam operations to mitigate downstream eutrophication.

This is further illustrated by focusing on the month of July, that is, during peak thermal stratification. As seen in Figure 5.7, Top water withdrawal through the dam is predicted to generate a near-linear increase in PRE from 19% for the baseline water level (i.e., 0 m) to 78% when water level is raised to +9 m, before declining slightly at +10 m. By contrast, for Normal and Bottom withdrawal and baseline water level, the reservoir acts as a net TP source (PRE -29% and -33%, respectively). This trend can be reverted by raising the water level above +5 m, with PRE reaching 28-30% at +10 m. These results reflect the impacts of two coupled mechanisms: (1) increasing the water level lengthens WRT to about 149 days, and (2) surface withdrawal prevents the downstream passage of the phosphorus-rich hypolimnetic water.

While dam operation can help reduce riverine P loads, potential trade-offs should be taken into consideration. Elevated water levels increase WRT, hence providing more time for organic P mineralization and, therefore, more in-reservoir P recycling, including from the reservoir bottom sediments. During July–August stratification, our simulations show bottom waters $\text{DO} < 2 \text{ mg/l}$ for up to 48 days, a condition typical for Fanshawe reservoirs (Nürnberg, 2007; Nürnberg & Lazerte, 2005, 2006). Under such prolonged anoxia, July–August sediment P fluxes in our model ranged from 10 to 32 $\text{mg P /m}^2 \text{ /d}$, with an annual mean of 8.7 $\text{mg P /m}^2 \text{ /d}$. These values fall within reported ranges for internal P loading in freshwater bodies, including 0–54 (Orihel et al., 2017), 0–52 (Nürnberg, 1988), 0–80 (Christophoridis & Fytianos, 2006), and 6–26 $\text{mg P /m}^2 \text{ /d}$ (Carter & Dzialowski, 2012). Consequently, while higher water levels combined with Top outflow effectively reduce the downstream P export, they can simultaneously cause worsening in-reservoir eutrophication and water quality issues linked to DO depletion.

Overall, in order to balance enhancing PRE against the risks related to intensified hypoxia and anoxia, we recommend: (1) raising water level and directing outflow through the surface gates specifically during peak stratification (e.g., in July PRE comes close to 80% for +9 m water level and Top withdrawal), and (2) during the remainder of the year impose only moderate water level rises (e.g., +2 m) to extend WRT while minimizing the duration of anoxia. Such an adaptive operational dam management should be guided by high time resolution monitoring of the depth distributions of temperature and DO.

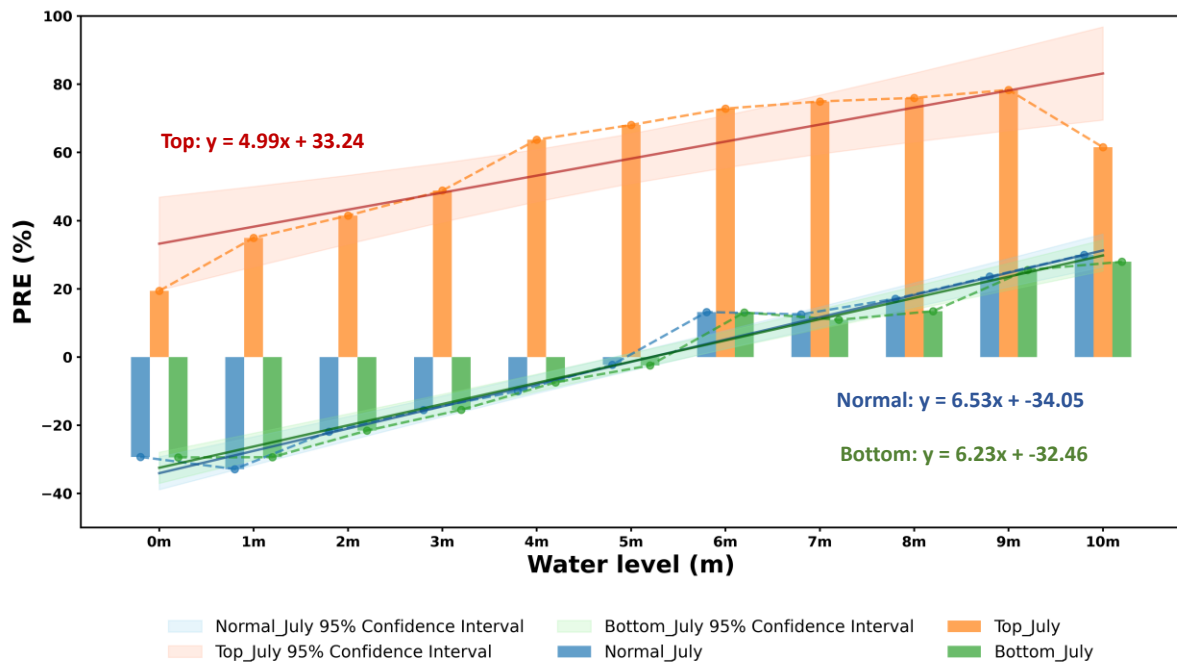


Figure 5.7. Model-predicted total phosphorus retention (PRE) for the month of July for the different scenarios. Colors identify the outflow conditions: blue = Normal, orange = Top, and green = Bottom. For each of the water levels from 0 to 10 m, the PRE values are indicated by the end-points of the bars. The lines are linear regressions through the PRE values for the three outflow conditions considered.

5.5.2 C-Q relationships and reactive particulate phosphorus

Concentration-discharge (C-Q) relationships are commonly used to characterize and compare the behavior of chemical constituents along the river continuum (Godsey et al., 2009; Knapp et al., 2020; Speir et al., 2024; Q. Zhang et al., 2016). For instance, the C-Q relationships reveal contrasting

mobilization patterns for DRP and TP in the river inflow to Fanshawe Reservoir: DRP exhibits a runoff mobilization (or enrichment) trend while TP shows more of a dilution trend. However, for both DRP and TP, the C-Q relationships downstream of the dam converge toward chemostatic trends. In other words, the in-reservoir P cycling decouples the concentrations of DRP and TP from variations in the riverine flow regime.

In the previous study by Kao et al. (2022), the difference in DRP:TP ratio between inflow and outflow of Fanshawe Reservoir was used as a measure of the change in P bioavailability due to the in-reservoir biogeochemical processing. The rationale was that DRP is the P pool that can directly be assimilated by plants, including algae. The values of DRP:TP measured by Kao et al. downstream of the dam during the peak stratification period in the summer were in the range 0.3-0.4, indicating that a large fraction of TP is exported from the reservoir in a highly reactive form.

A major biogeochemical process in the reservoir is photosynthetic fixation of DRP into algal biomass. The resulting biomass-associated P can rapidly be mineralized back to DRP when the algal detritus is degraded. Thus, the particulate P leaving the reservoir also contains a reactive fraction that can become bioavailable and fuel primary production in downstream aquatic ecosystems. To provide an estimation of the importance of the reactive particulate P pool, we used the algal biomass P computed by CE-QUAL-W2 under the baseline scenario (Normal outflow; 0 m water level; Figure D.11). The ratio of the algal biomass P to TP begins to climb around Julian day ≈ 150 in both years as high surface irradiance, warm temperatures and nutrient-rich conditions stimulate algal production. Using a 30-day simple moving average (SMA) to smooth out outliers, maximum summer values of the ratio are in the 0.2-0.3 range. Over the full 2018–2019 record, the mean value is around 0.10. These results imply that Fanshawe Reservoir systematically shifts the exported TP toward more bioavailable forms in summer, both in the dissolved and particulate fractions.

5.5.3 Retention estimates and model limitations

Previous studies support significant P retention by Fanshawe reservoir on an annual basis but also report seasonal occurrences of enhanced P export relative to the inflow (Kao et al., 2022; Nürnberg & Lazerte, 2015, 2005, 2006). Using the Weighted Regressions on Time, Discharge and Season with Kalman Filter (WRTDS-K) method to estimate inflow and outflow P loads, Kao et al. (2022) derived annual PRE values of 25 and 47% for 2018 and 2019, respectively. These values are higher than the average annual PRE obtained here (13% under baseline scenario).

The reason for the difference in PRE between the two different approaches, the statistical gap filling of concentration data by Kao et al. (2022) and our mechanistic modeling, is not entirely clear. It could at least in part be due to biases in the load estimations of Kao et al. Re-running WRTDS-K on the TP data for Fanshawe Reservoir reveals a positive bias (+0.47, ~50% overestimation) for the inflow TP loads and a negative bias (-0.13, ~15% underestimation) for the outflow TP loads (Figure D.12). These biases imply that the previously estimated PRE values may have been too high.

Acquisition of additional data time series will be needed to further calibrate and test the CE-QUAL-W2 model. There also remains scope to verify the performance of the default mathematical representations of the various biogeochemical processes in the model, and to assess the sensitivity of the results to both the model structure and parameter values. However, the general agreement of the model simulations with the available data supports the use of CE-QUAL-W2 as a diagnostic and prognostic tool that could help guide watershed-scale nutrient management.

5.6 Conclusions and perspectives

Like many reservoirs worldwide, Fanshawe Dam must reconcile multiple socio-ecological objectives, flood control, power generation, and recreation, while also protecting aquatic ecosystems against the impacts of eutrophication (Giuliani et al., 2021; Yin et al., 2011). While previous studies have usually focused separately on the response of nutrient cycling to water level adjustment (He et al., 2022; H. Wang et al., 2024) and selective water withdrawal (Lindenschmidt et al., 2019; Song et al., 2023), our scenario modeling shows that combining water level control with selective redirecting dam outflow may yield greater P retention efficiency than relying on either control lever alone. Yet, at the same time, management practices that increase PRE may intensify hypolimnetic hypoxia and anoxia and, therefore, promote greater internal P loading. These practices, therefore, must be weighed against operational mandates and possible risks to in-reservoir water quality.

Overall, our study confirms the potential of using adaptive dam operation for P control in reservoirs. It also highlights that effective control strategies must build on a robust and predictive understanding of the reservoir's hydrodynamics and, in particular, that of the duration and strength of water column stratification. Because the underlying mechanisms follow basic physical principles, the approach illustrated here for Fanshawe Reservoir should, in principle, be directly transferable to the many thousands of small and medium-sized run-of-river reservoirs worldwide that experience seasonal hypoxia.

Equally important, our results call for incorporating dynamic operational dam scenarios into catchment-scale nutrient models and into the science-policy dialogues on the sustainable management of the Laurentian Great Lakes and, more broadly, global lake eutrophication mitigation. Doing so will ensure that reservoir management is recognized—and optimized—as a potential tool in nutrient-reduction portfolios. Future work should explore multi-objective optimization that couples water-quality targets with flood-control, hydropower, and recreation goals, and it should test whether the operational options, such as those proposed here, can be automated through the use of virtual (in-silico) reservoir twins.

Chapter 6

Summary and Perspectives

6.1 Summary of major findings

Below, I provide an overview of the main findings from each chapter, highlighting how the research goals outlined in Chapter 1 have been addressed throughout my thesis.

In Chapter 2, I integrated global datasets and developed the Global Reservoir Modeling (GRM) database through a multithreading framework. This work consolidates large-scale global data to support hydrological and biogeochemical modeling for over 6,800 reservoirs worldwide. The GRM database comprises 40 years (1980-2019) of high-resolution climate data, water temperature data, discharge data, and considers three types of reservoir bathymetry. I illustrated the use of GRM by simulating decade-long trends in global reservoir surface temperatures. The results indicate, on average, an increase of 0.47°C per decade for reservoir surface temperature. Importantly, GRM provides researchers and practitioners with a platform that couples data with process models, enhancing large-scale modeling capabilities for dam reservoirs.

Building on the initial work of Chapter 2, in Chapter 3, I provide more detailed results about the changes in thermal structure of global reservoirs over the past 40 years. The mean surface-to-bottom temperature differential rose from 8.95°C in 1980 to 10.50°C in 2019—a decadal increase of 0.39°C that intensified after 2000 (0.57°C per decade vs. 0.22°C per decade in 1980–2000). Surface layers warmed at 0.47°C per decade compared to 0.10°C at bottom layers, driving stronger stratification. Concurrently, the global mean thermocline deepened from 15.9 m to 17.1 m at a rate of 0.30 m per decade, indicating epilimnion thickening and reduced mixing. Correlation analyses show air temperature dominates surface warming, while inflow and dew-point temperatures more strongly influence deep layers. Regional breakdown reveals hypolimnetic warming accelerated with climate: cold-class reservoirs warmed by $+0.36^{\circ}\text{C}$ (1980-2000) and $+0.65^{\circ}\text{C}$ (2000-2019), and temperate-class by $+0.08^{\circ}\text{C}$ and $+0.46^{\circ}\text{C}$, respectively—signaling weakened winter mixing and prolonged summer isolation, with critical implications for oxygen dynamics and nutrient cycling.

Chapter 4 introduces GLRDAV, a global archive of depth–area–volume relationships for over 1.4 million lakes and reservoirs. By merging shoreline polygons (HydroLAKES) with bathymetric estimates (GLOBathy), GLRDAV provides >17 million regression equations—five polynomial functions (orders 1-5) and one power function—at 0.1 m depth intervals for each lake and reservoir. Validation against ReGeom, GRDL, and in situ surveys confirms that higher-order polynomials (orders 4-5) yield the lowest RMSE and highest R^2 , while simpler functions suffice for small

waterbodies. The accompanying “Global Waterbody Calculator” Python package enables rapid retrieval of coefficients and generation of model-ready bathymetry grids.

In Chapter 5, we apply our automated modeling workflow in Chapter 2 and an improved bathymetric mesh in CE-QUAL-W2 to simulate 33 combinations of water level (0 to +10 m) and withdrawal locations at Fanshawe Reservoir. Under baseline conditions (normal outflow, no water level change), the reservoir retains 13% of incoming total phosphorus (TP) annually and becomes a net TP source in summer. Switching to surface withdrawal raises annual TP retention to 20% and combining surface withdrawal with a +10 m water level increase boosts summer TP retention above 78% and annual retention to 52%. These gains result from a fourfold extension of hydraulic residence time—peaking at 149 days—and effective hypolimnetic isolation.

In conclusion, these chapters demonstrate that integrated big-data frameworks and high-resolution bathymetric relationships enable realistic, process-based modeling of global reservoirs; that climate-driven warming has measurably intensified stratification with uneven regional impacts; that high-resolution depth–area–volume relationships and tools are essential for accurate three-dimensional simulations; and that local-scale applications of these frameworks can yield actionable insights for effective reservoir management under changing climate conditions.

6.2 Future work

6.2.1 Global freshwater quality applications

Future work would involve exploring additional water quality modeling applications of the GRM database and the D-A-V relationships developed in this thesis. These tools offer high-resolution inputs for process-based models such as CE-QUAL-W2 and similar hydrodynamic-ecosystem models. By integrating GRM and D-A-V with these models, it becomes possible to simulate key environmental variables—including water temperature, nutrient concentrations, dissolved oxygen, and contaminants—considering different bathymetries and hydrometeorological conditions. For example, emerging pollutants such as microplastics could be tracked along river systems using GRM's capabilities by integrating microplastic emission factors with transport calculations and retention in lakes and reservoirs (Earn et al., 2021; Lebreton et al., 2017; Nava et al., 2023). Additionally, by integrating data sourced from climate datasets such as ERA5 and CMIP6 (Hersbach

et al., 2020; O'Neill et al., 2016), more detailed and accurate reconstructions of water quality changes over time could be obtained.

The combination of GRM and D-A-V facilitates scaling from regional studies to global models, offering a consistent framework for analyzing water quality in lakes and reservoirs worldwide. Future applications could further explore how D-A-V-derived parameters enhance predictions of water storage and pollutant retention, enabling more accurate simulations across various spatial scales. By coupling the outputs from GRM and GLRDAV with process-based modeling, it would become possible to conduct detailed tracking of water quality parameters under multiple scenarios, ranging from seasonal shifts to long-term climatic changes. Such capabilities would enable researchers and water managers to anticipate water quality trends, identify vulnerabilities, and tailor management practices accordingly. These multi-scale, integrative approaches should help increase the predictive accuracy of regional hydrological models, ultimately supporting more robust frameworks for sustainable water resource management.

A further extension of the GRM framework would be to incorporate existing wetland datasets, such as the Global Wetland Database. Wetlands play a critical role in nutrient cycling and pollutant filtration; however, they are also susceptible to accumulating pollutants, including heavy metals and (Lehner et al., 2025; Lehner & Döll, 2004) microplastics (X. Zhang et al., 2024). By integrating wetland-specific data with GRM, researchers could develop enhanced models to evaluate wetland health and resilience in response to changing local, regional and global anthropogenic pressures.

6.2.2 Global waterbodies machine learning application

The GRM and D-A-V outputs developed in this thesis could provide a rich dataset for exploring data-driven machine learning (ML), paving the way for new continental-scale modeling approaches. Future work will build ML models on these datasets to detect patterns and forecast water quality in real time. Data-driven ML approaches would open new opportunities to fill current gaps in process-based models, allowing for adaptive, real-time predictions of water body conditions across diverse geographical and climatic settings.

Furthermore, coupling ML-informed environmental models with large language models (LLMs) could enable the development of interactive, forecasting tools for public use (Ray, 2023; Ren et al., 2024). These tools could provide predictive insights and early warnings regarding water quality changes, pollution events, and potential ecosystem impacts. Such systems could deliver real-time predictions for

stakeholders, including water resource users, decision-makers, and the general public, enhancing the accessibility and usability of freshwater data. This approach paves the way for a data-driven, user-friendly freshwater modeling platform.

6.2.3 Global water management applications: digital twins

Recent advances in big data and AI have driven digital twins in watershed management, irrigation, and reservoir operations. Currently, most implementations target individual reservoirs or local sites. They focus on basic tasks—flow control, flood management, and water-level monitoring. Future work will use the GRM database, Chapter 5 simulations, and batch-processing code to build digital twin visualizers for lakes and reservoirs. Integrating nutrient cycling, P loading, DO, and temperature stratification into digital twins enables real-time visualization for government and industry.

Developing digital twins faces three challenges: modeling dynamic water quality, handling real-time data volumes, and ensuring interoperable interfaces. This work demands collaboration between water scientists, computer engineers, and visualization experts.

The GRM and water quality models form a robust backend. They integrate with Vue.js, React, Flask API, and other frameworks. This approach empowers government, industry, and the public with data-driven management tools. Digital twins improve decision-making, reduce eutrophication, and support sustainable reservoir management. Moving forward, integrating digital twin technologies with emerging AI capabilities, such as machine learning and large language models (Ray, 2023; Ren et al., 2024), could further enhance predictive capabilities, providing early warning systems and decision-support tools that benefit both policymakers and the public. The ongoing evolution of digital twin platforms promises substantial improvements in sustainable global water management, fostering resilience and adaptability in freshwater ecosystems worldwide.

6.3 Moving towards global long-term effects of sediments in waterbodies

A major area for future study lies in understanding the global, long-term impacts of sediment interactions within lakes and reservoirs, including the role of sediments in nutrient cycling, pollutant retention, and groundwater exchange. Currently, due to computational resource, measurement, and modeling limitations, sediment and water-quality models apply mainly at local scales (Auer et al., 1993; Jin et al., 2019; Søndergaard et al., 2003; Z. Xu et al., 2020; Q. Zhang et al., 2016). Global groundwater and surface water quality coupling is still a relatively underdeveloped area, and there is

no effective integration for long-term, global-scale studies. However, advancements in global climate reanalysis data, such as ERA5-Land, provide a basis for developing sediment models tailored to reservoir systems.

Incorporating simplified box sediment models into global freshwater models, such as the GRM, is a promising approach for expanding the scope of research beyond local applications. Sediment models, when combined with process-based hydrodynamic models and high-resolution datasets could enhance the accuracy of predictions concerning the interaction between sediment layers and overlying water, particularly for nutrient and contaminant fluxes. This integration would enable a better understanding of how sediment accumulation affects water quality over extended timescales, including the long-term effects of aging reservoirs and sediment buildup in lakes and wetlands.

Furthermore, the underrepresentation of groundwater dynamics in current large-scale models poses a significant challenge. Groundwater plays a critical role in water quality, especially in regions where groundwater and surface water interact extensively (Brookfield et al., 2021). While many frameworks now include groundwater–surface water exchanges, key gaps remain in constraining flux magnitudes and parameterizations across diverse hydrogeologic settings, as well as in standardized, observation-based evaluation at scale. (Benz et al., 2024; Condon et al., 2021)

By providing a cohesive database and modeling framework, the GRM enables future work on sediment and groundwater dynamics, supporting an integrated approach to understanding the long-term effects of these factors on water quality. Such insights are critical for addressing the evolving challenges of freshwater management under changing environmental and anthropogenic conditions, ultimately fostering sustainable water quality practices. Developing global-scale sediment models in lakes and reservoirs, improving the coupling between surface and groundwater systems, and utilizing big data approaches are key to advancing our understanding of the long-term dynamics of sediments in global waterbodies.

Code and Data Availability

All datasets utilized in my research have been made publicly available on the Federated Research Data Repository (FRDR) to ensure future research and reproducibility. Each chapter references specific datasets, which can be accessed via the following links:

Chapter 2

GlobalReservoirModel V1.0-V1.3 A new global reservoir modeling database. Federated Research Data Repository. <https://doi.org/10.20383/103.0792>

Chapter 4

Global lakes depth-area-volume relationship with 0.1m resolution. Federated Research Data Repository. <https://doi.org/10.20383/103.0881>

Chapter 5

Modeling Phosphorus Cycling in a Seasonally Stratified Reservoir (Fanshawe Reservoir, Ontario, Canada). Federated Research Data Repository. <https://doi.org/10.20383/102.0321>

All code supporting my study is also accessible upon request or through the repository.

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Appendix A: Supplementary Material: Chapter 2

1. GRM user manual:

GRM readme file summary:

The detailed GRMreadme file is compiled with GRM database in FRDR

(1) File List

GRM data/year/Reservoir ID/model usable files

----/GRM_run_public.py

----/GRM_wsc-public.py

----/data_public

----/logs

(2) Relationship between files, if important:

Yearly folders store all reservoir model useable files:

- Bth.csv, bth1-3.csv: Reservoir bathymetric files with different shapes
- DLX: Segment lengths (m)
- ELWS: Water surface elevation (m)
- PHI0: Segment orientation
- FRIC: Bottom friction
- LAYERH: Layer Heights (m)

Notes: All reservoirs in GRMV1.0_1980_2000 and GRMV1.0_V1.3_data feature bth.csv files. However, only in GRMV1.0_V1.3_data can one find the bth_1, bth_2, and bth_3.csv files. Notably, some reservoirs in GRMV1.0_V1.3_data lack these specific files due to gaps in the original data.

- Tin_xxx.csv: Water temperature with inflow. XXX is the version of FutureStream database(Bosmans et al., 2022);
- JDAY: Julian Day
- Tin: Inflow water temperature (°C)
- Met.csv: Daily climate data
- TAIR: Air temperature (°C)
- TDEW: Dewpoint temperature (°C)

- WIND: Wind speed (m/s)
- PHI: Wind direction (Rad)
- CLOUD: Cloud cover
- Qin and Qot.csv: Inflow and outflow information;
- JDAY: Julian day
- QIO: Inflow and outflow (m³/s)

W2_con.npt, wsc.npt, shade.npt, graph.npt: CE-QUAL-W2 model control files and parameters, please see detailed information in Cole and Wells 2017.

- GRM_run_public.py: Concurrently simulating all reservoirs

GRM_wsc-public.py: Generating wind coefficient for all reservoirs

- Data_public: CE-QUAL-W2 V4.1 pre-exe and exe files; Graph.npt and shade.npt are the default parameters in CE-QUAL-W2. Users can modify them with specific reservoirs.

2. Figure supplementary:

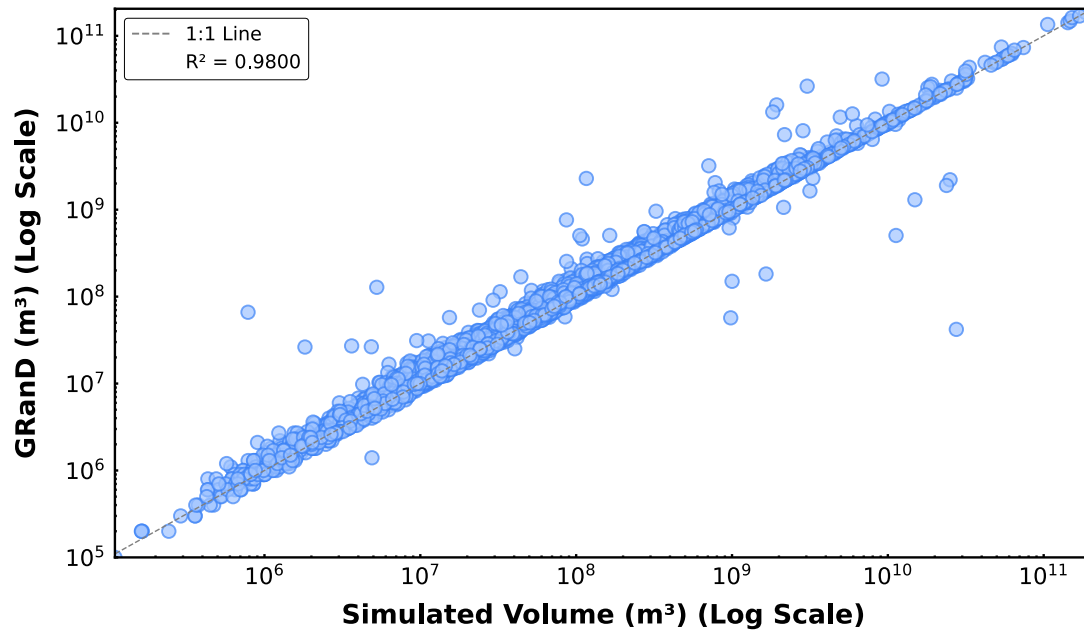


Figure A.1. Bathymetric data validation: Trapezoidal total volume vs GRanD database.

Appendix B: Supplementary Material: Chapter 3

1. Supplementary method:

(1) Gradient's equations:

Gradients were calculated by dividing these temperature differences by the corresponding layer height (ΔZ), providing a standardized measure of thermal variation across layers.

Temperature difference:

$$\text{Temperature Difference } (\Delta T_{i,j}) = T_i - T_j$$

Temperature gradient:

$$\text{Temperature Gradient } (G_{i,j}) = \frac{\Delta T_{i,j}}{\Delta Z_{i,j}}$$

where T_i and T_j are temperature at layer i and j . $\Delta Z_{i,j}$ is the height difference between layers i and j .

(2) Equations for Bayesian Multivariate Regression:

Regression Model:

Modeled water temperature (y_i) for observation i in each layer:

$$y_i \sim N(\mu_i, \sigma)$$

And the mean temperature (μ_i) specified as a linear combination of input variables:

$$\mu_i = \alpha + \sum_{j=1}^p \beta_j x_{ij}$$

Where y_i is the target variable (temperature) for observation i ; x_{ij} is the value of input variable j for observation i . α is the intercept parameter. β_j is the regression coefficient for input variable j . σ is the noise term representing observation-level variability.

Priors:

Weakly informative priors assigned to all model parameters:

$$\alpha \sim N(0, 10), \quad \beta_j \sim N(0, 10), \quad \sigma \sim \text{HalfNormal}(1)$$

Where the normal priors for α and β_j reflect an expectation of small but non-zero effects for the predictors. The half-normal prior for σ restricts the noise term to non-negative values with a reasonable scale.

Likelihood:

Likelihood for the observed temperature outputs (y):

$$p(y | \alpha, \beta, \sigma, X) = \prod_{i=1}^n \mathcal{N}(y_i | \mu_i, \sigma)$$

where:

- n is the total number of observations,
- y_i is the observed temperature at instance i ,
- μ_i is the model-predicted mean temperature, typically defined as $\mu_i = \alpha + \sum_{j=1}^p \beta_j x_{ij}$,
- X are the variables,
- α is the intercept term of the model,
- β is the regression coefficient (slope),
- σ is the standard deviation of the Gaussian noise,

Parameter Estimation:

Posterior sampling was performed using the No-U-Turn Sampler (NUTS), a variant of the Hamiltonian Monte Carlo method (Hoffman & Gelman, 2014). I ran 2,000 draws with 1,000 tuning steps for each layer.

Convergence diagnostics:

Convergence diagnostics, such as the Gelman-Rubin statistic ($\hat{R}$), were examined to ensure proper mixing and convergence of the chains.

Results Analysis and Visualization:

Posterior Summaries: For each parameter, we computed the posterior mean and 95% Highest Density Interval (HDI).

Data Export: The regression coefficients and trace summaries were saved to CSV format files for further analysis.

2. Supplementary figure:

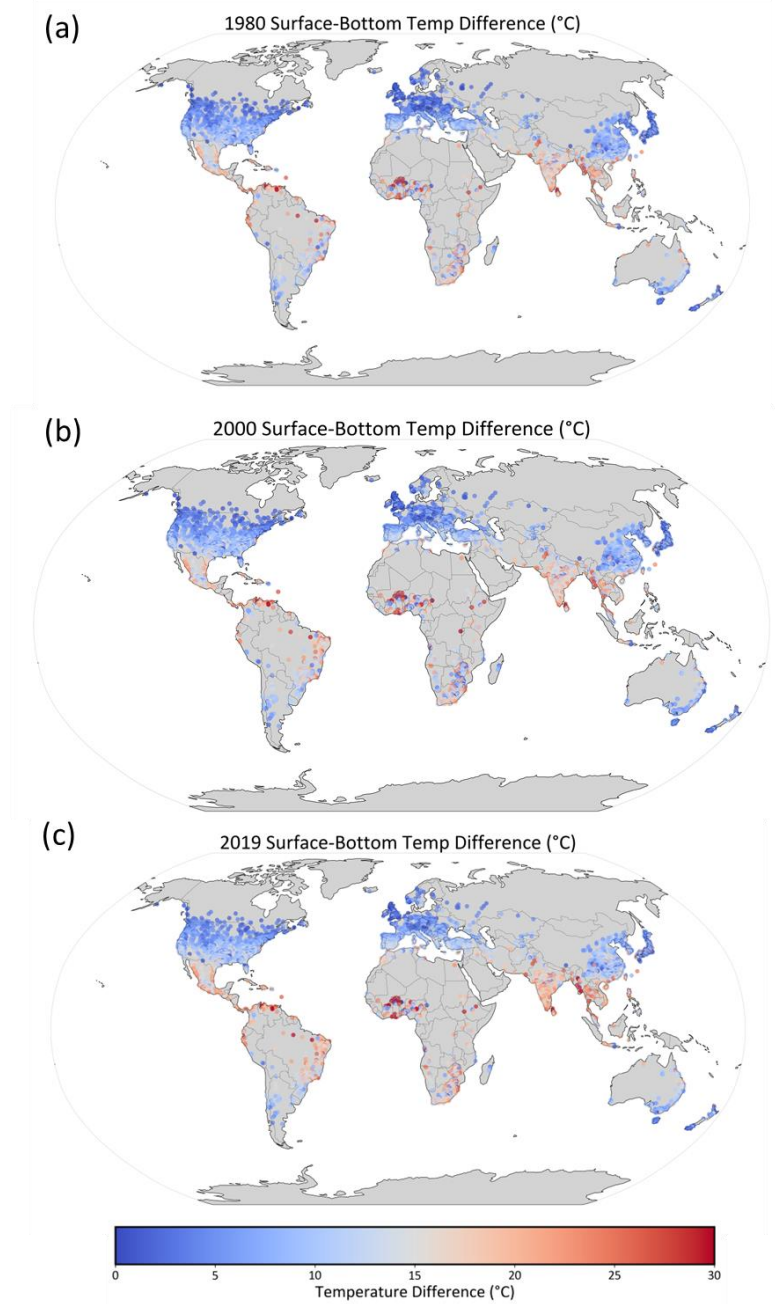


Figure B.1. Global distribution of surface-to-bottom temperature differences (ΔT , °C) in GRM reservoirs for (a) 1980, (b) 2000, and (c) 2019. Cooler colors (blue) indicate lower ΔT , whereas warmer colors (red) indicate higher ΔT .

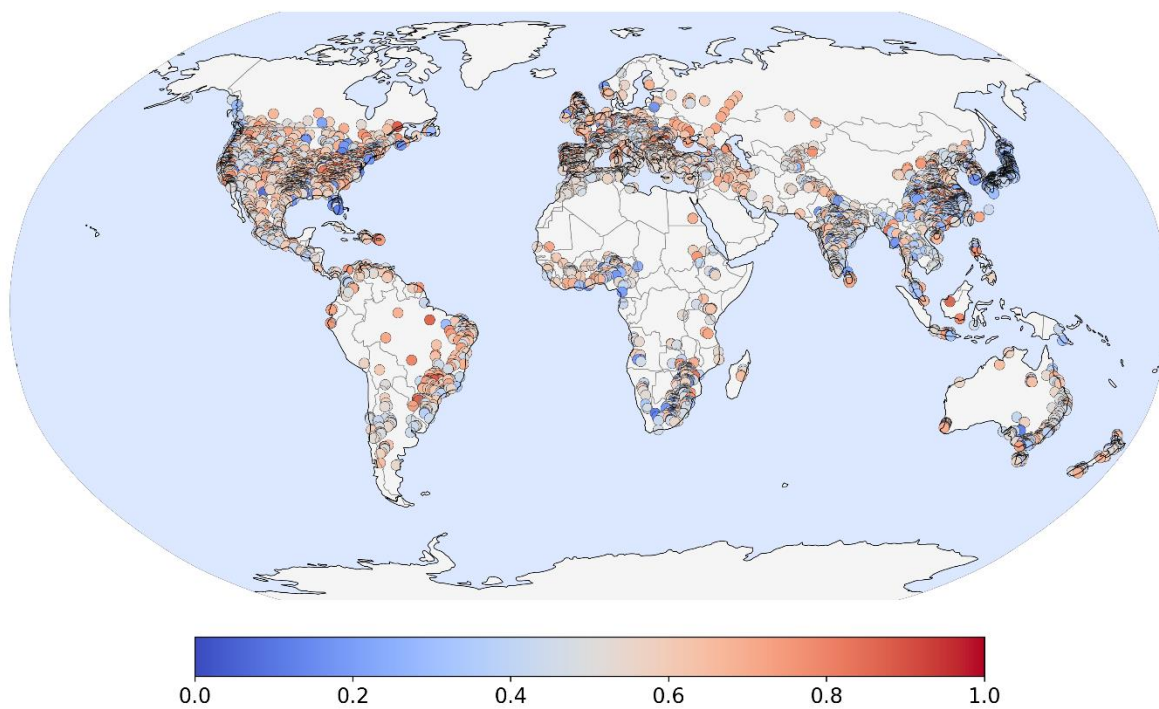


Figure B.2. Global distribution of maximum gradient depth variations (log normalized) for the year 2000.

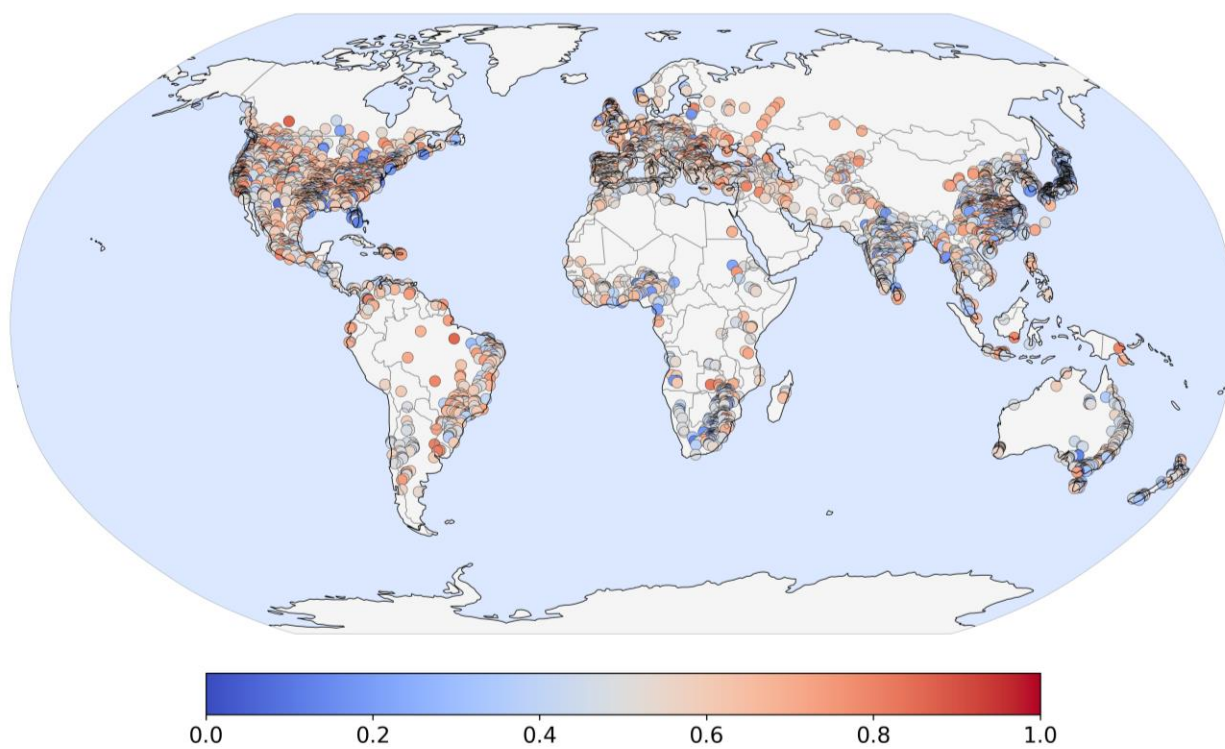


Figure B.3. Global distribution of maximum gradient depth variations (log normalized) for the year 2019.

Table B.1. Köppen–Geiger climate-zone statistics of the surface-to-bottom temperature difference (ΔT) for 1980 and 2019, and of the change $\Delta\Delta T = \Delta T_{(2019)} - \Delta T_{(1980)}$, across GRM reservoirs (mean, median and standard deviation). For each climate class (Tropical, Arid, Temperate, Cold, Polar) and Global. Note: sample size in the Polar class is small and estimates should be interpreted with caution.

Region	1980 mean (°C)	1980 median (°C)	1980 std (°C)	2019 mean (°C)	2019 median (°C)	2019 std (°C)	Δ (2019– 1980) mean (°C)	Δ (2019– 1980) median (°C)	Δ (2019– 1980) std (°C)
Tropical	15.91	16.07	5.99	17.42	17.72	6.00	1.51	1.39	1.92
Arid	11.35	10.66	6.00	12.66	12.28	6.05	1.31	1.19	1.77
Temperate	8.35	7.97	4.74	9.92	9.69	5.00	1.57	1.42	1.36
Cold	4.25	3.88	2.69	6.01	5.75	3.11	1.77	1.67	1.20
Polar	3.39	2.94	3.16	4.76	4.71	3.83	1.37	1.28	0.88
Global	8.95	8.01	5.86	10.51	9.72	5.97	1.56	1.41	1.49

Appendix C: Supplementary Material: Chapter 4

1. Supplementary tables:

Table C.1. Summary of global fresh waterbodies hydrological characteristics.

Continent	Type	Count	Total_Volume	Mean_Res_time	Mean_Ratio	Median_Ratio	Total_Lake_Area
Global	All	1351817	1.53E+08	1783.417	0.341067	0.302771	2525163
Africa	All	14284	28736348	1276.054	0.326801	0.253842	189957.7
Asia	All	57864	5657873	1924.831	0.293006	0.224037	224695.7
Europe	All	261650	80075070	2486.03	0.376932	0.339363	743723.3
North America	All	958710	34325322	1641.933	0.339429	0.303157	1199598
Oceania	All	9734	299514.5	2873.061	0.237954	0.195657	35432.22
South America	All	49575	3705349	578.4185	0.263915	0.197873	131756.3
Europe	Lake (NonCaspian)	261138	3687591	2489.409	0.376533	0.339076	321793.2
Africa	Lake	13849	27991502	1297.432	0.322072	0.24857	158241.8
Africa	Reservoir	435	744846.1	595.4552	0.47738	0.454721	31715.87
Asia	Lake	56952	4797084	1947.806	0.288279	0.221013	194165.4
Asia	Reservoir	912	860789.6	490.0842	0.588196	0.590132	30530.23
Europe	Lake	261139	79287591	2489.813	0.376533	0.339076	698795.1
Europe	Reservoir	511	787478.3	553.0413	0.58114	0.565233	44928.26
North America	Lake	957361	33212295	1642.531	0.339185	0.303009	1129598
North America	Reservoir	1349	1113027	1217.117	0.513019	0.497832	70000.39
Oceania	Lake	9604	240926	2895.338	0.233398	0.193683	32302.73

Oceania	Reservoir	130	58588.5	1227.306	0.574531	0.600855	3129.49
South America	Lake	49400	2972885	578.0397	0.263089	0.197265	98534.39
South America	Reservoir	175	732464	685.3411	0.497187	0.463275	33221.91

Table C.2. Comparative performance of D-A-V relationships: R² and RMSE compared with training dataset.

	Polynomial	Polynomial	Polynomial	Polynomial	Polynomial	
	Function	Function	Function	Function	Function	Power
Metric	Order 1	Order 2	Order 3	Order 4	Order 5	Function
R² (D-A)	0.9300	0.9815	0.9864	0.9908	0.9935	0.9612
R² (D-V)	0.8363	0.9943	0.9997	0.9999	0.9999	0.9810
RMSE (D-A)	0.22976	0.06145	0.03239	0.01955	0.01284	0.12072
RMSE (D-V)	0.02103	0.00435	0.00037	0.00015	0.00007	0.00483

In situ data comparison summary (Area unit: km², RMSE unit: mcm):

Table C.3. Statistical analysis of Cedar creek in situ data with GLRDAV regression results.

Metric	Model	RMSE	R²
Depth-Area	GRDL	23.01695	0.726266
Depth-Area	ReGeom	16.90552	0.85233
Depth-Area	Polynomial 1	18.26107	0.8277
Depth-Area	Polynomial 2	11.62189	0.930211
Depth-Area	Polynomial 3	11.88291	0.927041
Depth-Area	Polynomial 4	11.86833	0.92722
Depth-Area	Polynomial 5	11.86535	0.927256
Depth-Area	Power Function	18.26808	0.827567
Depth-Volume	GRDL	247.5164	-0.04385
Depth-Volume	ReGeom	64.8728	0.928294
Depth-Volume	Polynomial 1	132.4282	0.701193
Depth-Volume	Polynomial 2	80.19743	0.890415
Depth-Volume	Polynomial 3	78.15776	0.895918
Depth-Volume	Polynomial 4	78.53873	0.894901
Depth-Volume	Polynomial 5	78.53701	0.894906
Depth-Volume	Power Function	113.5115	0.780462

Table C.4. Statistical analysis of Coleman reservoir in situ data with GLRDAV regression results.

Metric	Model	RMSE	R²
Depth-Area	GRDL	2.256451	-3.78032
Depth-Area	ReGeom	0.653682	0.598821
Depth-Area	Polynomial 1	0.422658	0.83228
Depth-Area	Polynomial 2	0.572015	0.692801
Depth-Area	Polynomial 3	0.571066	0.693819
Depth-Area	Polynomial 4	0.583832	0.679977
Depth-Area	Polynomial 5	0.582394	0.681551
Depth-Area	Power Function	0.636685	0.619412
Depth-Volume	GRDL	14.11172	-10.2229
Depth-Volume	ReGeom	4.319339	-0.05143
Depth-Volume	Polynomial 1	2.524987	0.640694
Depth-Volume	Polynomial 2	2.344741	0.690161
Depth-Volume	Polynomial 3	2.340926	0.691168
Depth-Volume	Polynomial 4	2.386441	0.679042
Depth-Volume	Polynomial 5	2.38665	0.678986
Depth-Volume	Power Function	2.409027	0.672938

Table C.5. Statistical analysis of Hubbard creek in situ data with GLRDAV regression results.

Metric	Model	RMSE	R²
Depth-Area	GRDL	9.23523	-0.11578
Depth-Area	ReGeom	8.757765	-0.00339
Depth-Area	Polynomial 1	5.377537	0.621688
Depth-Area	Polynomial 2	5.479019	0.607275
Depth-Area	Polynomial 3	5.488064	0.605978
Depth-Area	Polynomial 4	5.486547	0.606195
Depth-Area	Polynomial 5	5.506609	0.60331
Depth-Area	Power Function	1.889661	0.953286
Depth-Volume	GRDL	47.7362	-0.74074
Depth-Volume	ReGeom	59.71937	-1.72438
Depth-Volume	Polynomial 1	16.90045	0.78181
Depth-Volume	Polynomial 2	7.717923	0.954497
Depth-Volume	Polynomial 3	7.202397	0.960373
Depth-Volume	Polynomial 4	7.028161	0.962267
Depth-Volume	Polynomial 5	7.00071	0.962561
Depth-Volume	Power Function	5.085508	0.980244

Table C.6. Statistical analysis of Lake Whitney in situ data with GLRDAV regression results.

Metric	Model	RMSE	R²
Depth-Area	GRDL	1.46278	0.712588
Depth-Area	ReGeom	1.937521	0.495758
Depth-Area	Polynomial 1	1.716182	0.604385
Depth-Area	Polynomial 2	1.612678	0.650665
Depth-Area	Polynomial 3	1.615815	0.649305
Depth-Area	Polynomial 4	1.615955	0.649245
Depth-Area	Polynomial 5	1.609402	0.652083
Depth-Area	Power Function	1.432792	0.724252
Depth-Volume	GRDL	2.304644	0.958399
Depth-Volume	ReGeom	9.107509	0.350333
Depth-Volume	Polynomial 1	6.012946	0.716817
Depth-Volume	Polynomial 2	4.114506	0.867405
Depth-Volume	Polynomial 3	4.049047	0.87159
Depth-Volume	Polynomial 4	4.049074	0.871589
Depth-Volume	Polynomial 5	4.051609	0.871428
Depth-Volume	Power Function	2.631349	0.945769

2. Readme and code:

Global Waterbody Calculator

****Global Waterbody Calculator**** is an open-source Python package for estimating storage curves and bathymetry of ****freshwater**** bodies.

Given a HydroLAKES ID or geographic coordinates, the tool fits global depth–area–volume (D-A-V) relationships, exports results, and generates high-resolution GeoTIFFs plus interactive 3-D visualizations.

[![PyPI](<https://img.shields.io/pypi/v/globalwaterbodycalculator.svg>)](<https://pypi.org/project/globalwaterbodycalculator/>)

[![License: MIT](<https://img.shields.io/badge/License-MIT-yellow.svg>)]([#license](#))

Features

| Capability | Details |

|-----|-----|

| Global D-A & D-V retrieval | Based on HydroLAKES, GLOBathy, GLRDAV |

| 0.1 m resolution | Area & volume at 0.1 m depth steps |

| Publication-ready plots | CSV and PNG outputs |

| Bathymetric GeoTIFF | Raster created from lake polygons |

| Interactive 3-D view | Matplotlib/Plotly surface rendering |

Installation

```
```bash
```

```
PyPI
```

```
pip install globalwaterbodycalculator
```

### ## Requirements

- Python  $\geq 3.7$

- Required packages (automatically installed via pip):

- `numpy`

- `pandas`

- `matplotlib`

- `scipy`

- `geopy`

- `rasterio`
- `scikit-learn`
- `gdal`
- `ogr`
- `shapely`

Ensure `GDAL` and `OGR` are installed and configured correctly on your system. These are required for raster and vector operations (e.g., shapefile processing and TIFF output).

## ## Quick Start (Python API)

```

python

from globalwaterbodycalculator.calculator import WaterBodyCalculator

Initialize the calculator

calculator = WaterBodyCalculator()

Calculate area-volume relationships by waterbody ID

result_df, water_body_id = calculator.calculate_area_volume(id=7, depth=244)

calculator.save_results_to_csv(result_df, water_body_id, output_dir='.')

calculator.plot_results(result_df, water_body_id, output_dir='.')

Alternatively, calculate using latitude and longitude

result_df, water_body_id = calculator.calculate_area_volume(latitude=45.59193, longitude=47.71771,
depth=10)

calculator.save_results_to_csv(result_df, water_body_id, output_dir='.')

calculator.plot_results(result_df, water_body_id, output_dir='.')

python

```

## ## Bathymetric Mapping and 3D Visualization

You can generate bathymetric maps and 3D plots from shapefiles:

```
``python
Generate bathymetric GeoTIFF and optionally plot 3D visualization
calculator.generate_bathymetry_tiff(
 lake_id=7, # Hylak_id of the waterbody
 shapefile='lakes.shp', # Location of the shp file
```

```

id_field='Hylak_id', # Name of the id column
depth=244, # Max depth of the waterbody
output_dir='output/',
plot_3d=True # Set to True to enable 3D plotting
)
...

```

This will:

- Compute the depth raster from the lake polygon and fitted D-A relationship
- Save the bathymetric map as a GeoTIFF
- Display an interactive 3D surface plot of the lake basin
- If "plot\_3d" is not set to True (default=False), only a GeoTIFF file will be generated

#### Input & Output

Item	Format	Description	
-----			
<b>**Input**</b>			
`id` <b>or</b> `latitude, longitude`	int / float	HydroLAKES ID or WGS-84 coordinates	
`depth`	float	Maximum depth (m)	
Lake polygon (optional)	ESRI Shapefile	Must include an `id_field` matching `Hylak_id`	
<b>**Output**</b>			
`<id>_dav.csv`	CSV	Depth, area (m²), volume (m³)	
`<id>_dav.png`	PNG	Area / volume curves	
`<id>_bathy.tif`	GeoTIFF	Bathymetric raster	
`<id>_3d.html`	HTML	Interactive 3-D view (optional)	

#### Directory Layout

globalwaterbodycalculator/

```

├─ calculator.py
├─ equations/ # reference equations
├─ examples/

```

└ docs/

## HydroLAKES download & licence

Global Waterbody Calculator does not redistribute the HydroLAKES shapefiles. "plot\_3d" need to use Hydrolakes Shapefile.

To run volume/area calculations or create maps you must:

Download the dataset from <https://www.hydrosheds.org/products/hydrolakes>.

Unzip it into a local folder (e.g. ~/data/HydroLAKES/).

Point the environment variable HYDROLAKES\_DIR to that path or pass the folder to the API/CLI option --hydrolakes\_path.

## Pypi Citations:

Please cite Global Waterbody Calculator in your publications as:

```
@software{Yu_Wu_Liao_Zhuo_GWC_2025,
 author = {Shengde Yu and Yukai Wu and Weikun Liao and Zhuo Zhijian},
 title = {Global Waterbody Calculator},
 year = {2025},
 version = {<0.1.3>},
 url = {https://pypi.org/project/globalwaterbodycalculator/}
}
```

## Appendix D: Supplementary Material: Chapter 5

### 1. Supplementary methods

The governing equations of hydrodynamic model and water quality model in CE-QUAL-W2 can be summarized as the following several equations

#### (1) Momentum equations:

The momentum equations include longitudinal and vertical equations. The lateral direction is average:

##### X-momentum (longitudinal):

$$\frac{\partial UB}{\partial t} + \frac{\partial UUB}{\partial x} + \frac{\partial WUB}{\partial z} = gB \sin \alpha + g \cos \alpha B \frac{\partial \eta}{\partial x} - \frac{g \cos \alpha B}{\rho} \int_{\eta}^z \frac{\partial \rho}{\partial x} dz + \frac{1}{\rho} \frac{\partial B \tau_{xx}}{\partial x} + \frac{1}{\rho} \frac{\partial B \tau_{xz}}{\partial z} + qBU_x$$

##### Z-momentum (vertical):

$$\frac{\partial W}{\partial t} + U \frac{\partial W}{\partial x} + V \frac{\partial W}{\partial y} + W \frac{\partial W}{\partial z} = g \cos \alpha - \frac{1}{\rho} \frac{\partial P}{\partial z} + \frac{1}{\rho \left( \frac{\partial \tau_{zx}}{\partial x} + \frac{\partial \tau_{zy}}{\partial y} + \frac{\partial \tau_{zz}}{\partial z} \right)}$$

where U is the horizontal velocity ( $\text{m s}^{-1}$ ), W is the vertical velocity ( $\text{m s}^{-1}$ ), g is the gravitational acceleration ( $\text{m s}^{-2}$ ), B is the channel width (m),  $\tau_x$  is the lateral average shear stress at x-direction ( $\text{kg m}^{-1} \text{s}^{-2}$ ),  $\tau_y$  is the y direction shear stress ( $\text{kg m}^{-1} \text{s}^{-2}$ ),  $\tau_z$  is the z direction lateral average shear stress ( $\text{kg m}^{-1} \text{s}^{-2}$ ),  $\rho$  is the density ( $\text{kg m}^{-3}$ ), P is the pressure, and  $\alpha$  is the channel slop (radian).

Here, the Z-momentum equation can be simplified as:

$$g \cos \alpha - \frac{1}{\rho} \frac{\partial P}{\partial z} = 0$$

The reason is the lateral direction is averaged, and the longitudinal length scale is much larger than the vertical length scale. Therefore, the W (vertical velocities) is much smaller than the U (horizontal velocities) and cancels out of the equation.

#### (2) Continuity equation:

$$\frac{\partial UB}{\partial x} + \frac{\partial WB}{\partial z} = qB$$

Where U is the horizontal velocity, (m s<sup>-1</sup>), W is the vertical velocity (m s<sup>-1</sup>), B is the channel width (m), q is the net lateral inflow per unit volume of cell (s<sup>-1</sup>).

### (3) State equation:

$$\rho = f(T_w, \phi_{TDS}, \phi_{ISS}) = \rho_T + \Delta\rho_s$$

Where  $\rho$  is the density (kg m<sup>-3</sup>), which is a function of temperature ( $\rho_T$ ), the concentration of total dissolved solids ( $\phi_{TDS}$ ), and the concentration of inorganic suspended solids ( $\phi_{ISS}$ ). Here,  $\Delta\rho_s$  represents the density increment due to solids.

The following relationship is applied in the model to represent the water temperature and density:

$$\begin{aligned} \rho_{T_w} = & 999.84 + 6.79 \times 10^{-2} T_w - 9.10 \times 10^{-3} T_w^2 + 1.00 \times 10^{-4} T_w^3 - 1.12 \times 10^{-6} T_w^4 \\ & + 6.54 \times 10^{-9} T_w^5 \end{aligned}$$

where  $\rho$  is density (kg m<sup>-3</sup>) and  $T_w$  is water temperature (°C).

### (4) Free surface equation:

This equation is related to the water surface elevation:

$$B_\eta \frac{\partial \eta}{\partial t} = \frac{\partial}{\partial x} \int_\eta^h UB \, dz - \int_\eta^h qB \, dz$$

where  $\eta$  is water surface depth (m), h is the depth (m), U is the horizontal velocity (m s<sup>-1</sup>), B is the channel width (m), q is the net lateral inflow per unit volume of cell (s<sup>-1</sup>).

### (5) Advection and diffusion equations:

$$\frac{\partial B\phi}{\partial t} + \frac{\partial UB\phi}{\partial x} + \frac{\partial WB\phi}{\partial z} - \frac{\partial \left( BD_x \frac{\partial \phi}{\partial x} \right)}{\partial x} - \frac{\partial \left( BD_z \frac{\partial \phi}{\partial z} \right)}{\partial z} = q_\phi B + S_\phi B$$

Where U is the horizontal velocity (m s<sup>-1</sup>), W is the vertical velocity (m s<sup>-1</sup>), B is the channel width (m),  $\phi$  is the laterally averaged constituent concentration (g m<sup>-3</sup>)  $D_x$  is the longitudinal temperature and constituent dispersion coefficient (m<sup>2</sup> s<sup>-1</sup>)  $D_z$  is the vertical temperature and constituent dispersion coefficient (m<sup>2</sup> s<sup>-1</sup>)  $q_\phi$  is the lateral inflow or outflow mass flow rate of constituent per unit volume (g m<sup>-3</sup> s<sup>-1</sup>)  $S_\phi$  lateral averaged source and sink term (g m<sup>-3</sup> s<sup>-1</sup>).

More detailed information can be found in the CE-QUAL-W2 user manual (Cole & Wells, 2017) and previous modeling developments conducted at Fanshawe reservoir (Yu, 2020).

#### **(6) Phosphorus (P) sediment model conceptual diagram and equations**

Here, we display sediment diagenesis model equation and diagrams in CE-QUAL-W2. All other P related equations can be found in CE-QUAL-W2 manual (Cole & Wells, 2017).

Layer 1 rate equation:

$$S_{po41} = 0$$

Layer 2 rate equation:

$$S_{po42} = \sum_{i=1}^3 k_{POPi} Y_{POPi} \Phi_{POPi}$$

where  $S_{po4}$  is the rate of phosphate in layer 1 or layer 2 (g m<sup>-3</sup> s<sup>-1</sup>);  $K_{POPi}$  is the particulate organic phosphorus class i mineralization rate (s<sup>-1</sup>),  $Y_{POPi}$  is the particulate organic phosphorus temperature rate multiplier (-),  $\Phi_{POPi}$  is the POP class i concentration, unit is g m<sup>-3</sup>.

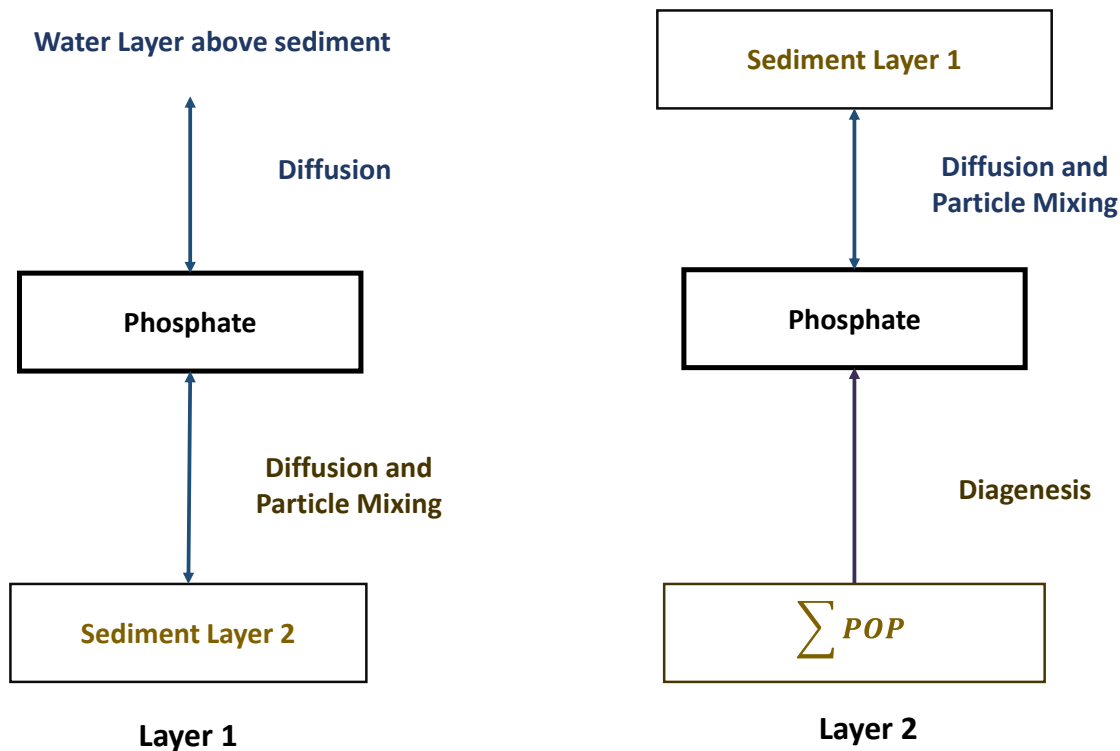


**Figure D.1. Phosphate internal flux of sediment diagenesis model in layer 1 (aerobic layer) and layer 2 (anaerobic layer). Modified from Cole and Wells, (2017).**

#### **(7) Supplementary explanation of phosphorus retention efficiency (PRE) calculation:**

We use the inflow concentration as the denominator for retention and the outflow concentration for release to have PRE numerical values that vary between 0 and 100% for both retention and release, hence making the extents of retention or release comparable to one another. We also used positive and negative signs to represent the retention and release events. This is best illustrated by the following numerical examples:

Assuming initial inflow TP and outflow TP are equal:

**Retention Event:** Consider a reservoir that increases the inflow TP concentration by a factor of 10. Using the inflow concentration as the denominator yields PRE = 90%; Using the outflow concentration as the denominator yields PRE = 900%.

**Release Event:** Consider a reservoir that increases the outflow TP concentration by a factor of 10. Using the inflow concentration as the denominator yields PRE = -900%. Using the outflow concentration as the denominator yields PRE = -90%.

Again, **Retention Event**: Consider a reservoir that reduces the outflow TP concentration to zero. Using the inflow concentration as the denominator yields retention  $PRE = 100\%$ . Using the outflow concentration as the denominator yields  $PRE = +\infty$ .

**Release Event**: Consider a reservoir that receives an inflow TP concentration of zero yet has a detectable outflow TP. Using the inflow concentration as the denominator yields  $PRE = -\infty$ . Using the outflow concentration as the denominator yields  $PRE = -100\%$ .

As these examples show, retention and release are weighted very differently when only using the inflow values as the denominator. By adjusting the calculation method and weighting approach, the PRE for retention and release events become comparable in numerical values. This provides more accurate metrics for evaluating the overall effectiveness of reservoirs in managing total phosphorus (TP). Switching between the denominators for retention and release and using positive and negative signs to distinguish between them, resolves the issue of different weighting for retention and release by the same factor.

#### **(8) Model calibration:**

The water level calibration was conducted using the water balance program from CE-QUAL-W2 V4.1, while the calibration of water temperature and dissolved oxygen (DO) utilized the wind shielding coefficient (WSC) file. Due to limited sediment phosphorus data, the current DRP and TP simulations were primarily based on parameter values recommended by the CE-QUAL-W2 model. Our current study focuses on the role of outlet flow and water levels in water quality management. Therefore, after refining the model's terrain accuracy, the parameters were selected based on previous modeling studies and the recommended values from the manual (Cole & Wells, 2017; Yu, 2020).

On July 9, 2018, three sediment cores were collected from Fanshawe Reservoir using a Universal Percussion Corer (Aquatic Research Instruments) to support the development of the current sediment diagenesis model. The average measured sediment bulk density and total phosphorus (TP) concentration were used to derive an initial particulate organic phosphorus (POP) concentration of approximately 150 mg/kg. In practice, the organic fraction of sedimentary P can vary greatly, particularly in agriculture-intensive watersheds where fertilizer application increases inorganic P loads. Based on Nürnberg and Lazerte's (2005, 2006) findings on the organic matter composition in Fanshawe Reservoir sediments, and

considering the dominant agricultural fertilizer inputs upstream, we assumed a 10% POP-to-TP ratio for the model. Due to limited sediment data, this 10% value was adopted in the present study.

## 2. Supplementary tables:

**Table D.1. Modeling waterbody volume.**

Name and Units	Values	Description
Hypsographic volume (m <sup>3</sup> )	13,146,000	Differences: 0.85%
Waterbody volume (m <sup>3</sup> )	13,034,250	
Branch 1 volume (m <sup>3</sup> )	12,603,332	Modeling Results
Branch 1 volume (m <sup>3</sup> )	430918	Modeling Results

**Table D.2. Waterbody location and initial conditions.**

Parameters Name and Units	Values	Description	Sources
Latitude	43.0326	Literature	Google Earth Pro
Longitude	81.1028	Literature	Google Earth Pro
Bottom Elevation (m)	250	Literature	UTRCA
Initial Temperature (°C)	0	Calibration	Initial temperature
Ice Thickness (m)	0.05	Default	Default and Calibration
Water Type	Fresh	Default	Cole and Wells (2017)

**Table D.3. Model performance metrics for water level, water temperature, DO, DRP, and TP: (a) Calibration year: 2018; (b) Validation year: 2019; (c) Overall performance.**

(a)

Metric (Units)	Modeled mean	Observed mean	ME	MAE	RMSE
Water level (m)	262.29	262.29	0.00	0.03	0.07
Water temperature (°C)	15.21	15.29	-0.07	1.13	1.39
Reservoir surface DO (mg/l)	10.44	10.20	0.24	0.60	0.72
Reservoir bottom DO (mg/l)	6.59	5.71	0.87	1.45	2.06
Reservoir surface DRP (mg/l)	0.01	0.02	-0.01	0.01	0.03
Reservoir surface TP (mg/l)	0.06	0.07	-0.02	0.04	0.05
Reservoir bottom DRP (mg/l)	0.02	0.02	-0.00	0.02	0.03
Reservoir bottom TP (mg/l)	0.07	0.08	-0.02	0.04	0.06

Downstream DRP (kg/day)	36.72	29.63	7.09	25.64	51.97
Downstream TP (kg/day)	152.45	98.39	54.06	80.13	149.60

(b)

<b>Metric (Units)</b>	<b>Modeled mean</b>	<b>Observed mean</b>	<b>ME</b>	<b>MAE</b>	<b>RMSE</b>
Water level (m)	262.51	262.47	0.04	0.06	0.09
Water temperature (°C)	14.81	15.09	-0.28	1.01	1.15
Reservoir surface DO (mg/l)	10.79	10.41	0.38	0.63	0.90
Reservoir bottom DO (mg/l)	8.78	7.54	1.24	1.59	1.98
Reservoir surface DRP (mg/l)	0.02	0.03	-0.01	0.01	0.03
Reservoir surface TP (mg/l)	0.07	0.11	-0.04	0.06	0.10
Reservoir bottom DRP (mg/l)	0.02	0.03	-0.01	0.03	0.04
Reservoir bottom TP (mg/l)	0.07	0.09	-0.02	0.06	0.10
Downstream DRP (kg/day)	201.49	161.58	39.91	69.86	169.71
Downstream TP (kg/day)	315.54	345.51	-29.97	124.46	272.16

(c)

<b>Metric (Units)</b>	<b>Modeled mean</b>	<b>Observed mean</b>	<b>ME</b>	<b>MAE</b>	<b>RMSE</b>
Water level (m)	262.40	262.38	0.02	0.04	0.08
Water temperature (°C)	15.03	15.20	-0.17	1.08	1.28
Reservoir surface DO (mg/l)	10.59	10.29	0.30	0.61	0.80
Reservoir bottom DO (mg/l)	7.86	6.77	1.09	1.53	2.01
Reservoir surface DRP (mg/l)	0.01	0.02	-0.01	0.01	0.03
Reservoir surface TP (mg/l)	0.06	0.09	-0.03	0.05	0.07
Reservoir bottom DRP (mg/l)	0.02	0.03	-0.01	0.02	0.03
Reservoir bottom TP (mg/l)	0.07	0.09	-0.02	0.05	0.08
Downstream DRP (kg/day)	144.57	116.00	28.57	54.59	140.66
Downstream TP (kg/day)	259.20	260.14	-0.94	109.15	237.09

**Table D.4. Correlation and P-values for water residence time (WRT), water temperature (WT), DO and TP with water levels control under different selective withdrawal scenarios.**

Month	WRT_normal		WRT_top		WRT_bottom	
	r	P-value	r	P-value	r	P-value
1	0.988	<0.01**	0.969	<0.01**	0.973	<0.01**
2	0.999	<0.01**	0.927	<0.01**	0.999	<0.01**
3	0.982	<0.01**	0.982	<0.01**	0.981	<0.01**
4	0.995	<0.01**	0.995	<0.01**	0.995	<0.01**
5	0.996	<0.01**	0.958	<0.01**	0.998	<0.01**
6	0.993	<0.01**	0.951	<0.01**	0.993	<0.01**
7	0.992	<0.01**	0.947	<0.01**	0.992	<0.01**
8	0.996	<0.01**	0.918	<0.01**	0.995	<0.01**
9	0.999	<0.01**	0.870	<0.01**	0.999	<0.01**
10	0.997	<0.01**	0.946	<0.01**	0.997	<0.01**
11	0.962	<0.01**	0.966	<0.01**	0.966	<0.01**
12	0.942	<0.01**	0.957	<0.01**	0.966	<0.01**

Month	WT_normal		WT_top		WT_bottom	
	r	P-value	r	P-value	r	P-value
1	0.975	<0.01**	0.934	<0.01**	0.857	<0.01**
2	-0.929	<0.01**	-0.408	0.213	-0.961	<0.01**
3	-0.003	0.992	-0.236	0.485	0.032	0.926
4	-0.971	<0.01**	-0.955	<0.01**	-0.939	<0.01**
5	-0.976	<0.01**	-0.886	<0.01**	-0.984	<0.01**
6	-0.993	<0.01*	-0.895	<0.01**	-0.987	<0.01**
7	-0.955	<0.01*	-0.904	<0.01**	-0.965	<0.01**
8	-0.894	<0.01**	-0.909	<0.01**	-0.902	<0.01**
9	0.933	<0.01**	-0.910	<0.01**	0.940	<0.01**
10	0.995	<0.01**	-0.101	0.768	0.997	<0.01**
11	0.933	<0.01**	0.963	<0.01**	0.943	<0.01**
12	0.553	0.078	0.164	0.630	0.567	0.069

Month	DO_normal		DO_top		DO_bottom	
	r	P-value	r	P-value	r	P-value
1	0.898	<0.01*	-0.036	0.916	0.947	<0.01**
2	0.998	<0.01**	-0.364	0.271	0.996	<0.01**
3	-0.278	0.409	-0.238	0.481	-0.371	0.262
4	-0.934	<0.01**	-0.245	0.469	-0.902	<0.01**
5	0.006	0.987	0.441	0.174	-0.201	0.553
6	-0.736	0.010	0.466	0.148	-0.806	<0.01**
7	-0.821	<0.01**	0.437	0.179	-0.865	<0.01**
8	-0.973	<0.01**	0.469	0.146	-0.961	<0.01**
9	-0.333	0.317	-0.157	0.645	-0.199	0.557
10	-0.953	<0.01**	-0.299	0.372	-0.954	<0.01**
11	-0.954	<0.01**	-0.518	0.103	-0.966	<0.01**
12	-0.799	<0.01**	0.030	0.930	-0.780	<0.01**

Month	TP_normal		TP_top		TP_bottom	
	r	P-value	r	P-value	r	P-value
1	0.970	<0.01**	0.898	<0.01**	-0.351	0.290
2	0.594	0.054	0.855	<0.01**	-0.796	<0.01**
3	-0.921	<0.01**	-0.949	<0.01**	-0.880	<0.01**
4	-0.748	<0.01**	-0.689	0.019	-0.670	0.024
5	0.981	<0.01**	0.804	<0.01**	0.986	<0.01**
6	0.971	<0.01**	-0.687	0.019	0.960	<0.01**
7	0.494	0.122	-0.941	<0.01**	0.693	0.018
8	0.321	0.336	-0.915	<0.01**	0.345	0.299
9	-0.952	<0.01**	-0.312	0.351	-0.917	<0.01**
10	-0.978	<0.01**	0.820	<0.01**	-0.970	<0.01**
11	-0.946	<0.01**	-0.817	<0.01**	-0.906	<0.01**
12	0.525	0.097	0.159	0.640	0.493	0.124

\*\* p<0.01 considered statistically significant

**Table D.5. Annual PRE for Normal, Top, and bottom scenarios under water level control (WLC).**

WLC(m)	Normal	Top	Bottom
0	13%	20%	14%
1	15%	25%	18%
2	18%	29%	21%
3	21%	33%	24%
4	24%	37%	27%
5	26%	40%	30%
6	29%	44%	33%
7	31%	46%	36%
8	34%	48%	39%
9	35%	51%	41%
10	37%	52%	43%

**Table D.6. Information on sediment cores (Site 1 is located closer to the dam, site 2 is at the midpoint of the reservoir, whereas site 3 is situated further upstream).**

Site ID	Storage of Core	Core #	Location of Core	Sectioned Depth available for analysis
Site 1	Freeze-dried	1	43.042467, -81.180362	71.6cm
Site 1	Frozen in -80°C	2	43.042417, -81.180231	54.8cm
Site 2	Frozen in -80°C	1	43.054364, -81.170036	39cm
Site 2	Freeze-dried	2	43.0543965, -81.1703775	49.5cm
Site 3	Frozen in -80°C	1	43.063102, -81.185980	50.3cm
Site 3	Freeze-dried	2	43.063192, -81.185885	55cm

### 3. Supplementary figures:

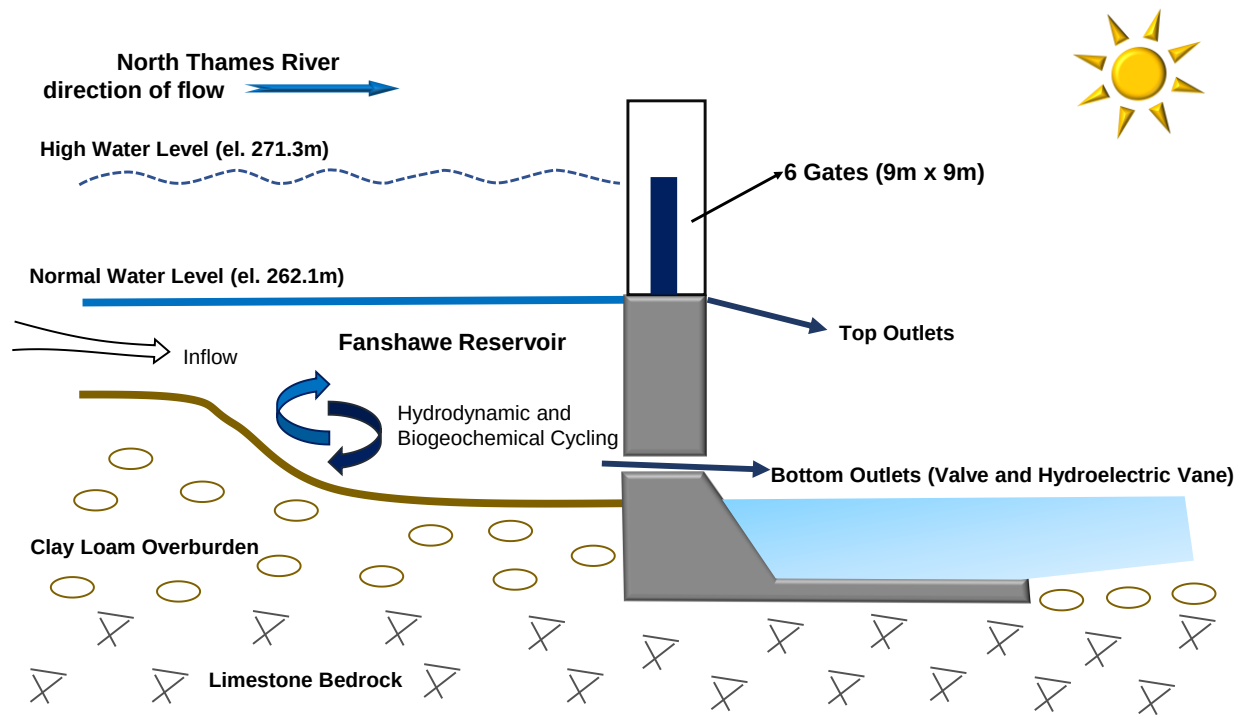
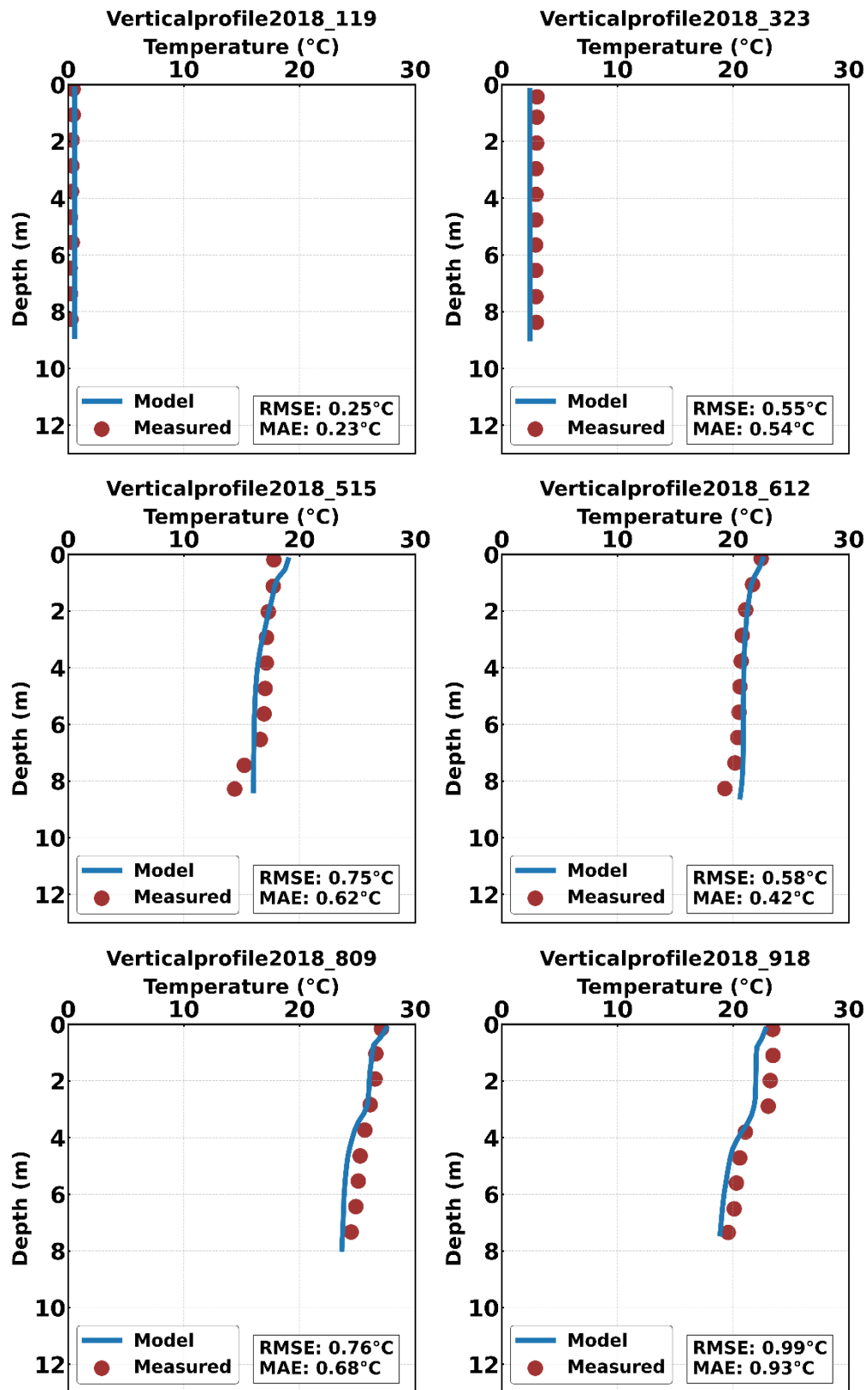


**Figure D.2. Fanshawe dam and reservoir conceptual diagram with water level operational and dam outlets information: Normal water level is around 262.1m; High Water level is around 271.3m.**



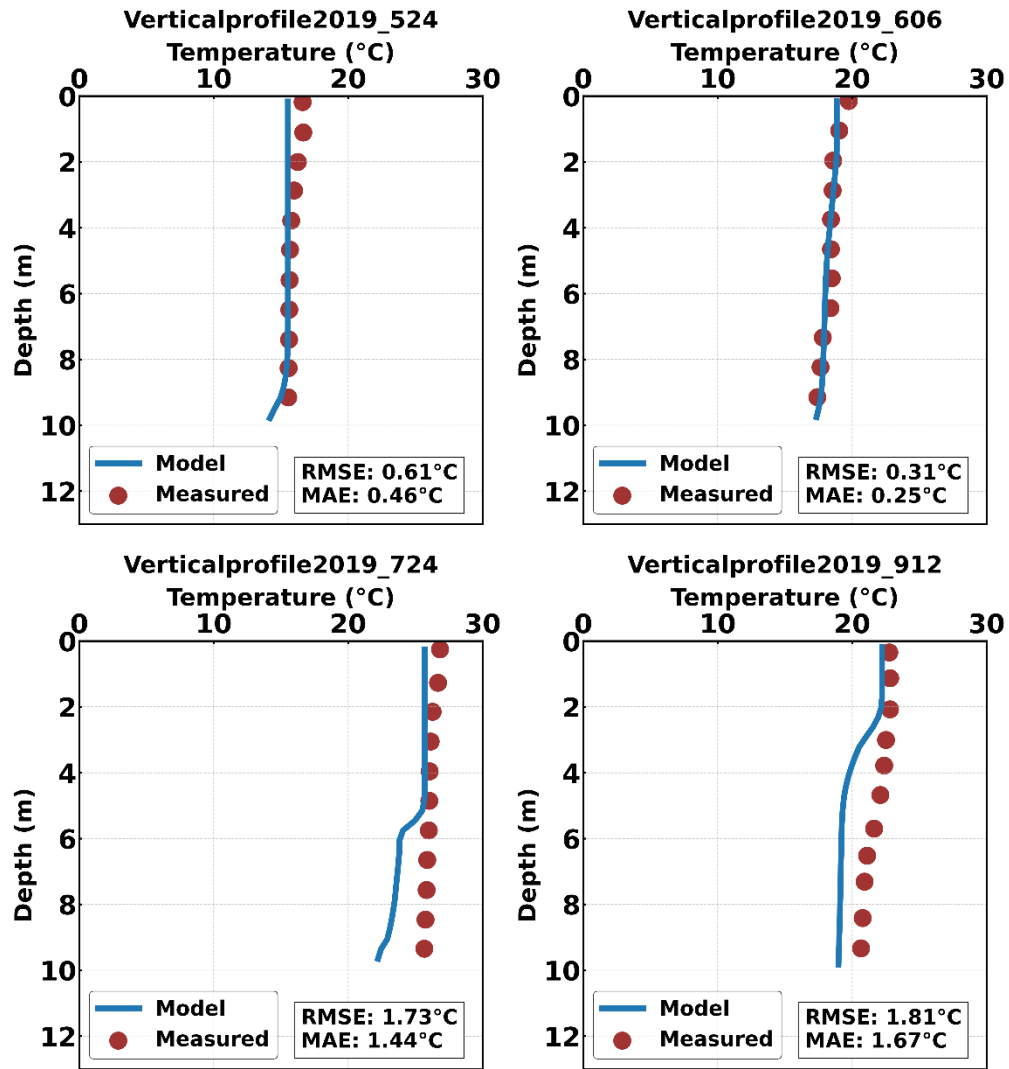


Figure D.3. Profile water temperature simulation results versus measured data in Fanshawe Reservoir from year 2018 to year 2019 (Modeling results: Blue lines; Measured data: Red points Vertical profile format: Year-Month-Day).

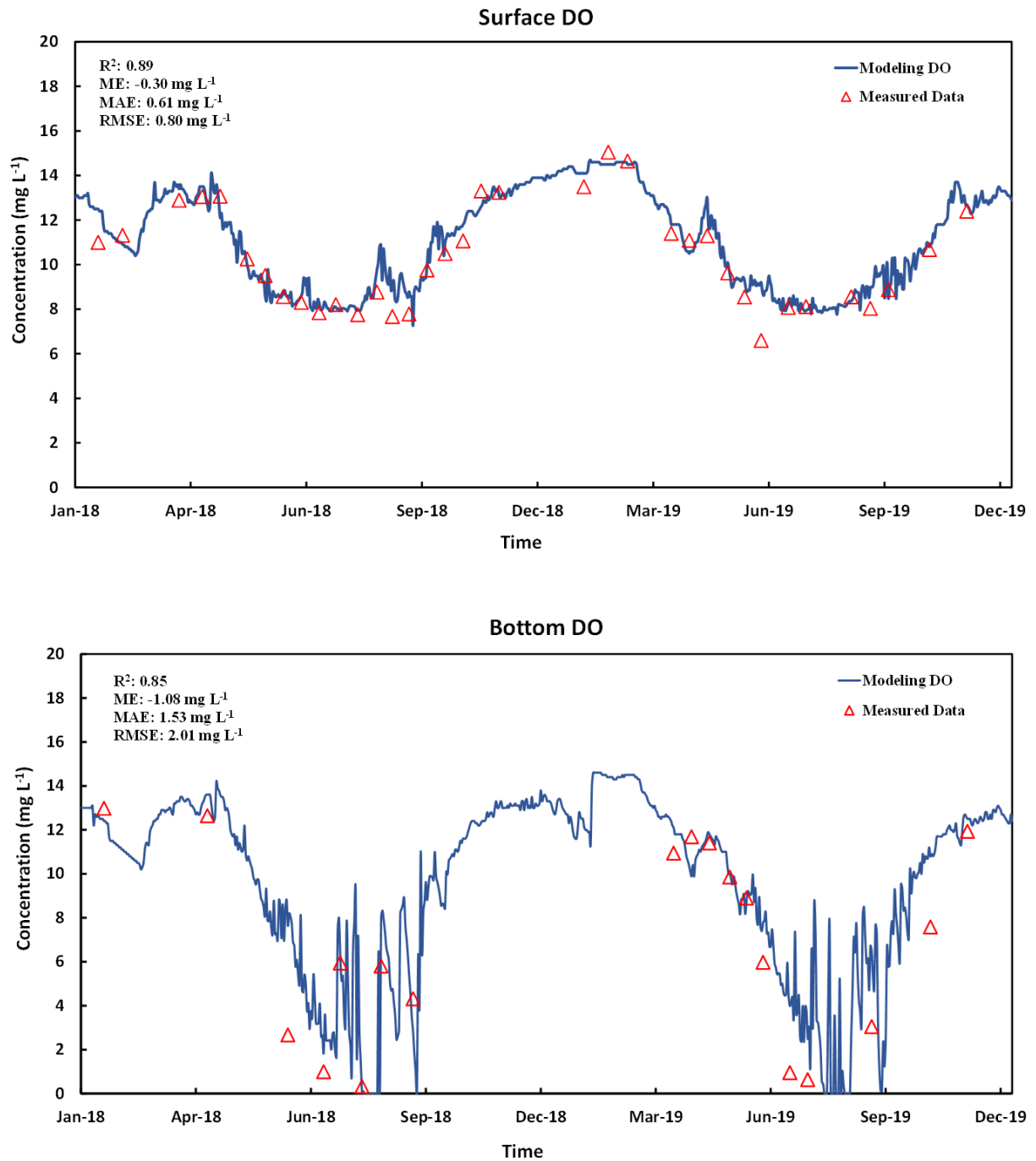


**Figure D.4. Surface and Bottom DO simulation results versus measured data in Fanshawe Reservoir from year 2018 to year 2019 (Modeling results: Blue lines; Measured data: Red triangles).**

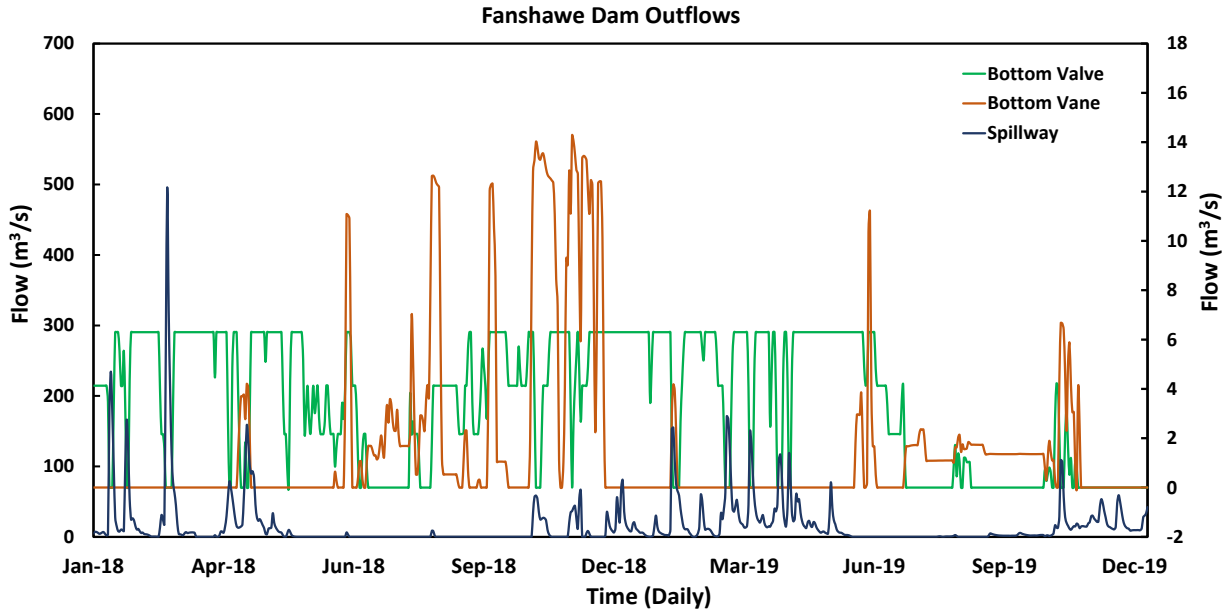


Figure D.5. Fanshawe Dam daily outflow from year 2018 to year 2019 – Normal outflow: Top outflow: blue lines plotted on the left axis; Bottom outlets: green and orange lines.

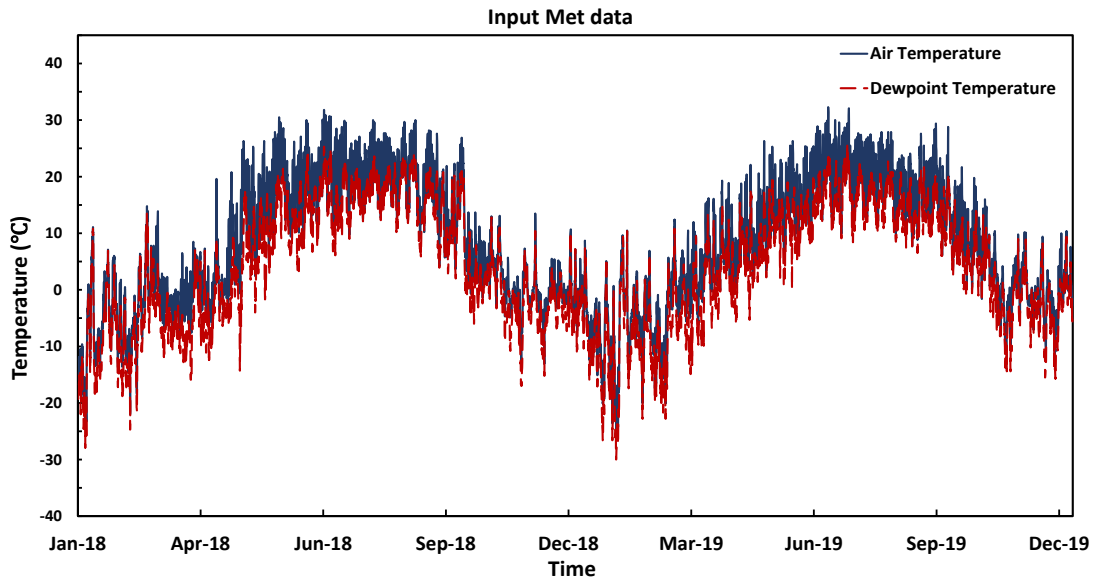


Figure D.6. 2018–2019 model input meteorological hourly data: Air and dewpoint temperature at London A station.

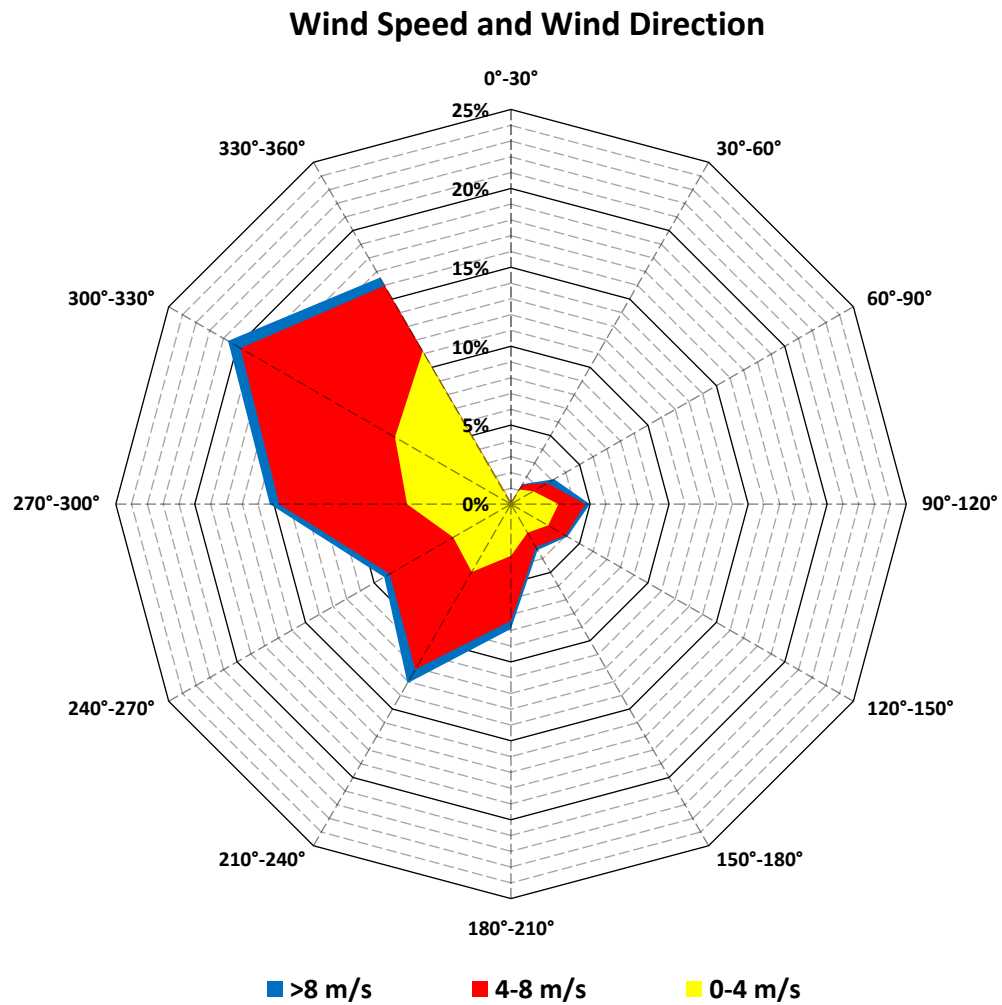


**Figure D.7. 2018–2019 model input meteorological hourly data: Wind rose diagram showing wind speed and direction information at London A station.**

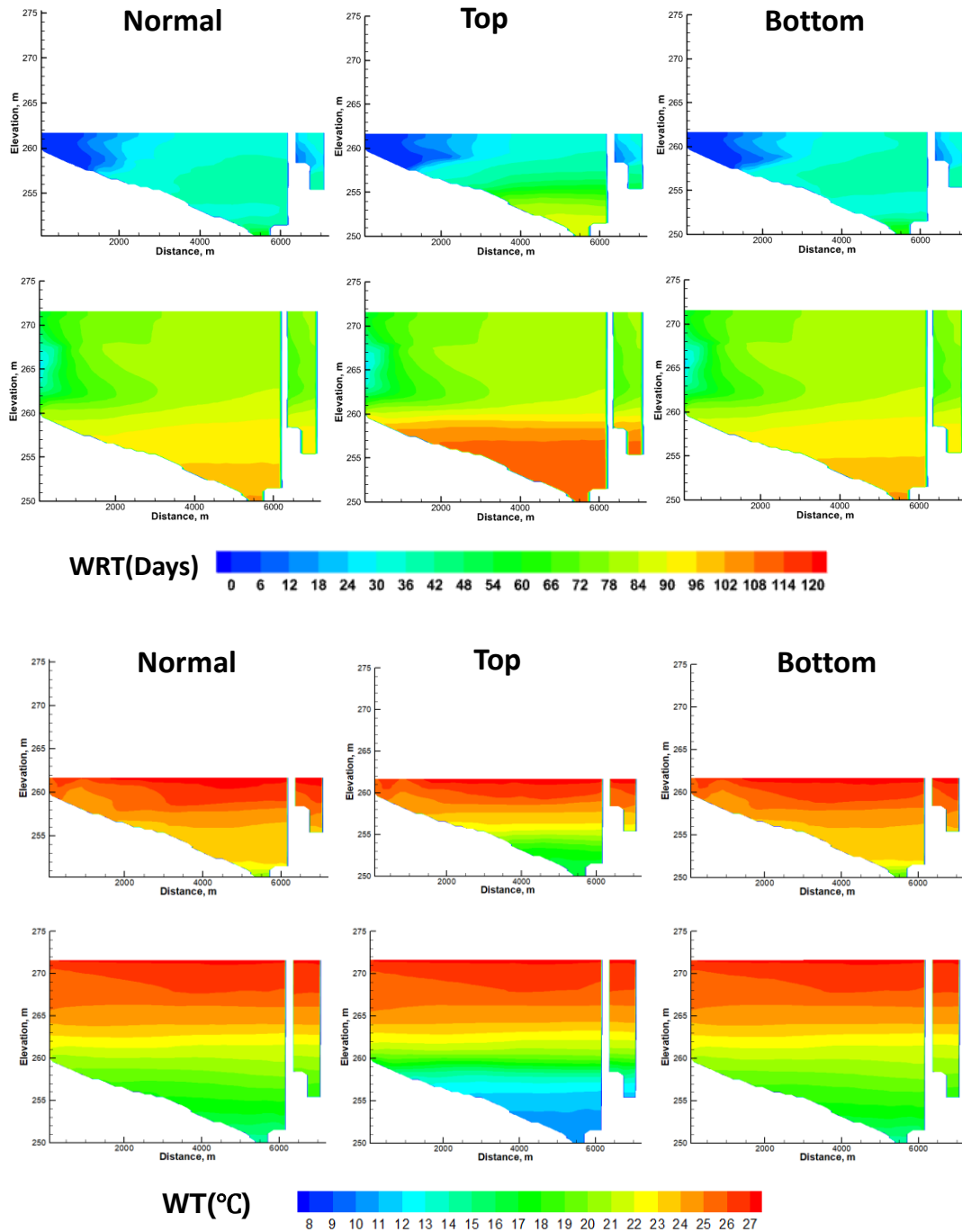


**Figure D.8. Comparative analysis of WRT and water temperature (WT) across different water levels and discharge scenarios during summertime: (1) Outflow scenarios: Normal: Standard dam operation outflow; Top: Total discharge from upper outflow; Bottom: Total discharge**

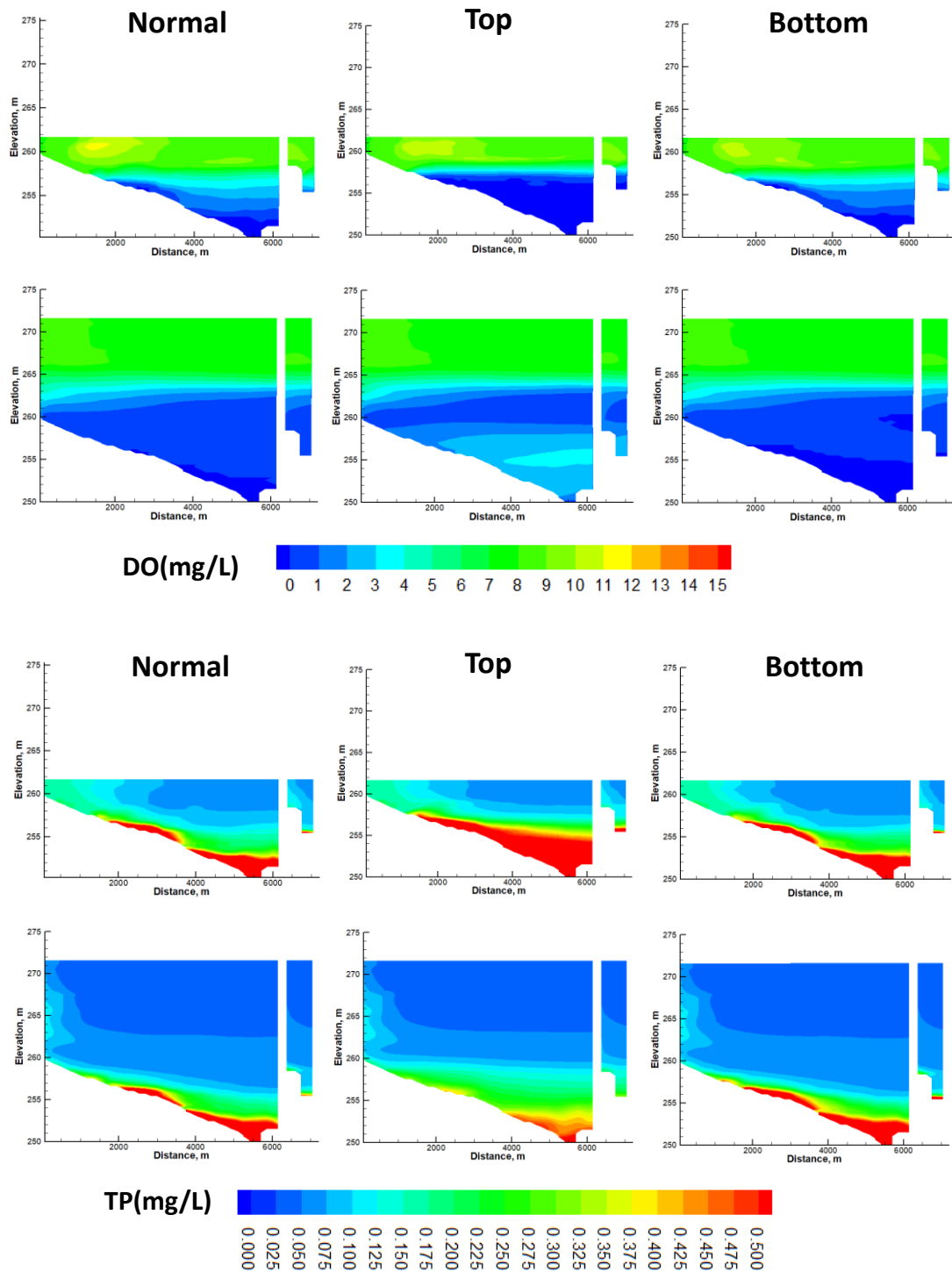


**Figure D.9. Comparative analysis of DO and TP across different water levels and discharge scenarios during summertime: (1) Outflow scenarios: Normal: Standard dam operation outflow; Top: Total discharge from upper outflow; Bottom: Total discharge from lower outflow.**

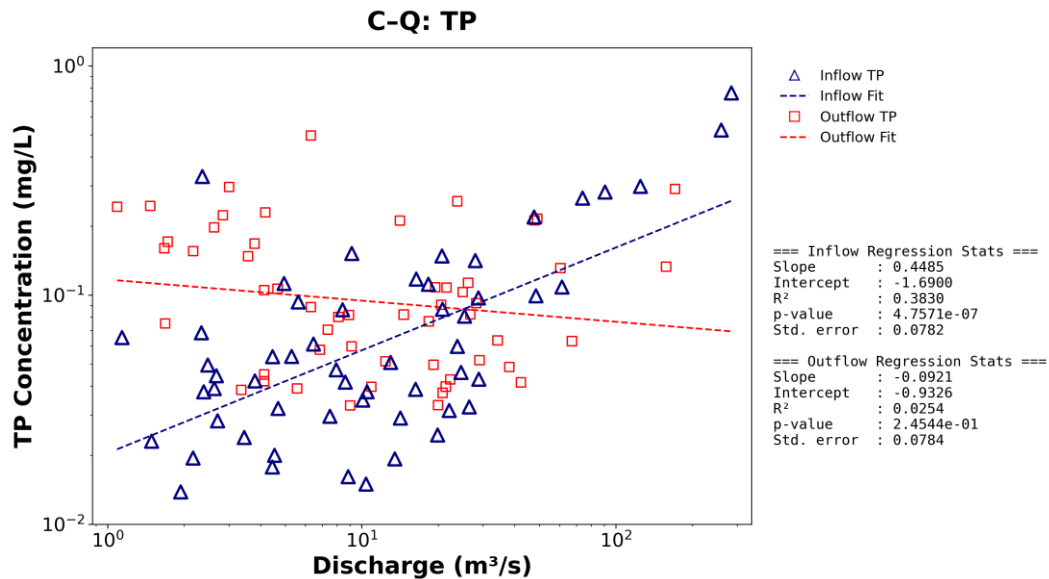


Figure D.10. Log-log concentration-discharge relationships for total phosphorus (TP) at Fanshawe Reservoir inflow and outflow. Blue triangles show inflow TP concentrations and red squares show outflow TP concentrations plotted against discharge (m³/s). Dashed lines are linear regression that fits on the log-transformed data.

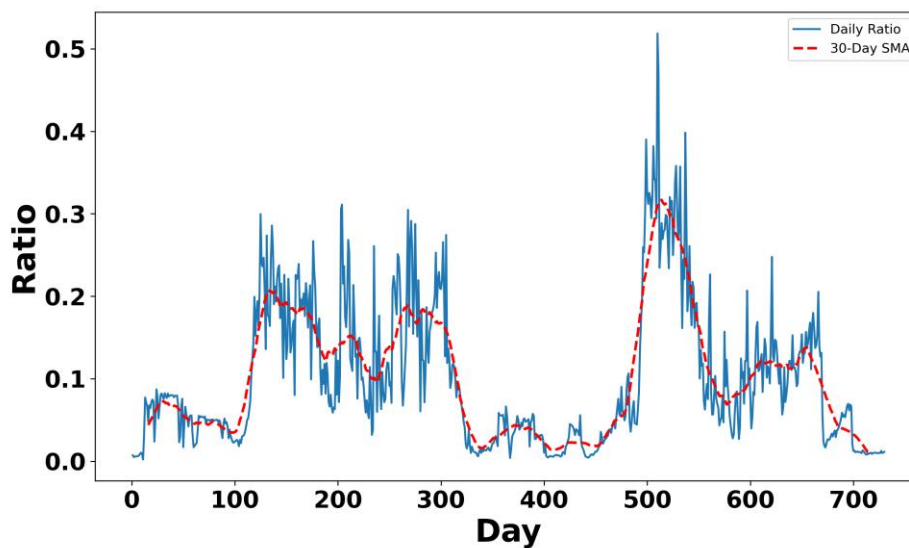


Figure D.11. Daily algal biomass P /TP flux ratio over a two-year period (blue line) with 30-day simple moving average (SMA, red dashed line).

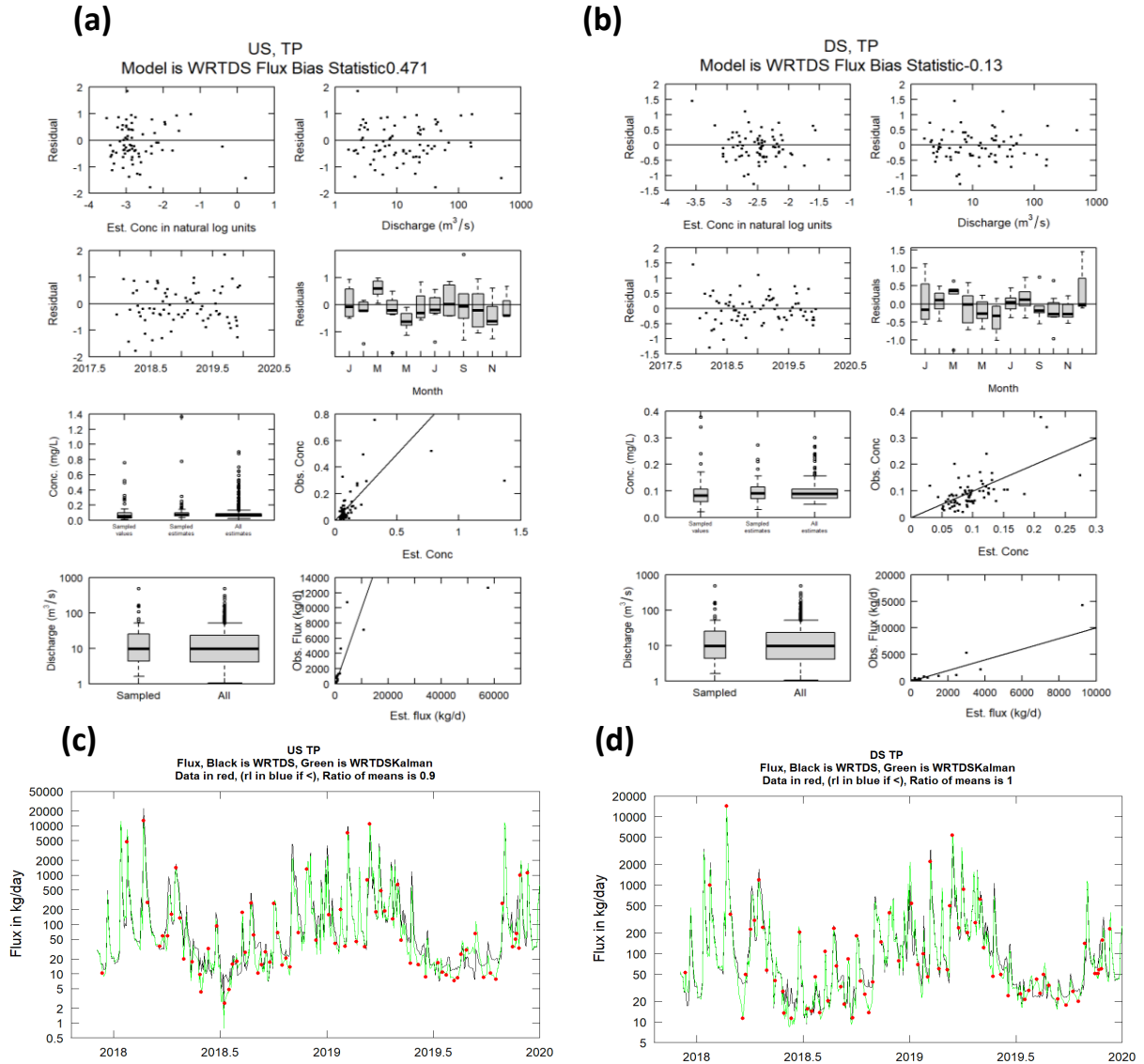


**Figure D.12. Diagnostic evaluation and phosphorus flux estimation using WRTDS and WRTDS-Kalman models for upstream (US) and downstream (DS) sites in Fanshawe Reservoir. (a–b) Residuals, concentrations, and flux-related diagnostics for TP at US (left) and DS (right) using the WRTDS model, including relationships with discharge, month, and estimated values. (c–d) Time-series comparison of TP flux (kg/day) between observed values (red dots), WRTDS estimates (black line), and WRTDS-Kalman smoothed results (green line) from 2018 to 2020.**

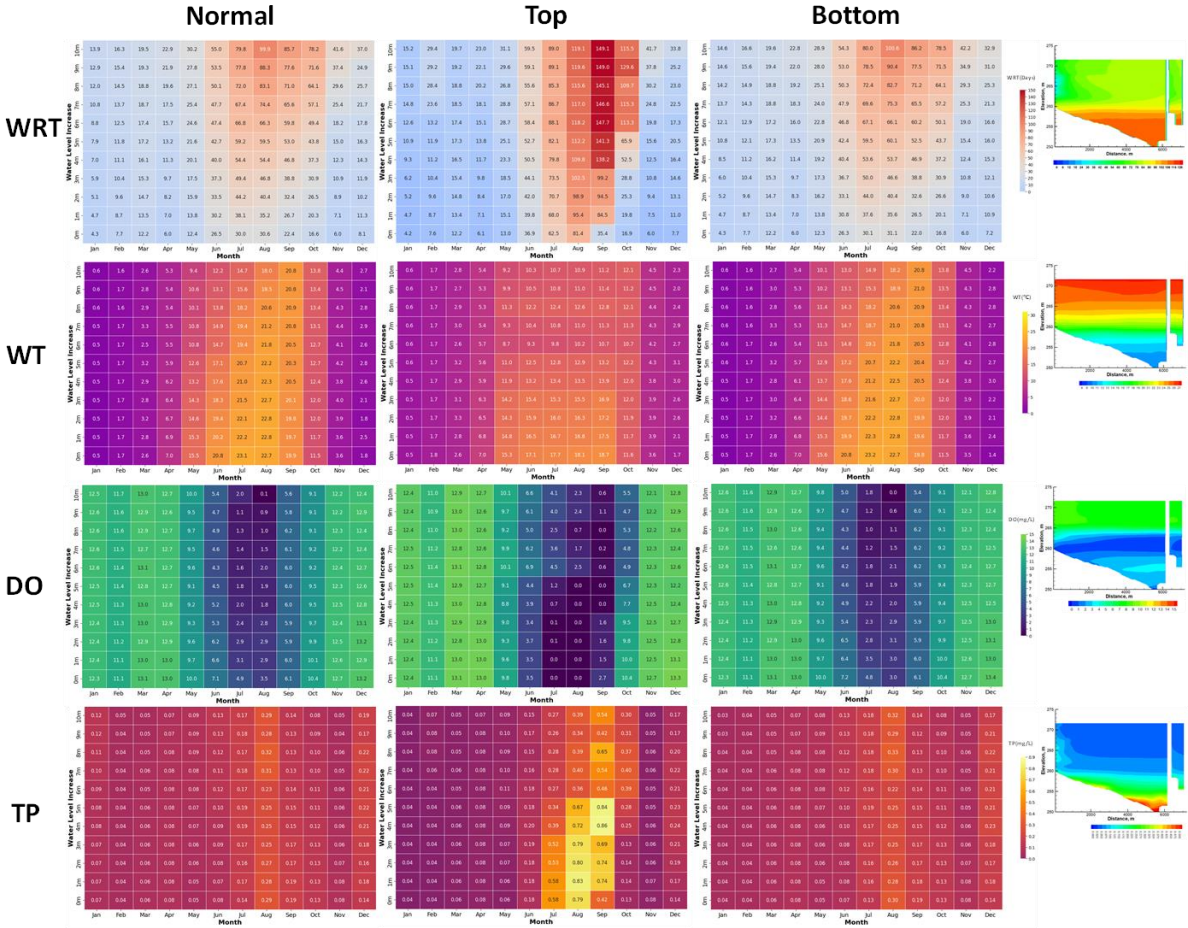


**Figure D.13. Comparative analysis of monthly bottom WRT, WT, DO, and TP across different water levels and discharge scenarios: (1) Outflow scenarios: Normal: Standard dam operation outflow; Top: Total discharge from upper outflow; Bottom: Total discharge from lower outflow. (2) Water level scenario: 0m-10m increasing by 1m at each scenario. (3) Profile map of WRT (days), WT (°C), DO, and TP (mg/l) for 10m\_water level at summertime on right.**