# Assessing the capability of UAV-borne multispectral and LiDAR sensors for mapping water levels in small water bodies

A thesis submitted to the College of Agriculture, Science and Engineering, at the University of KwaZulu-Natal, in partial fulfilment of the requirements of the degree of master's in

Environmental Science

Pietermaritzburg

South Africa

UNIVERSITY OF KWAZULU-NATAL ™

INYUVESI YAKWAZULU-NATALI

By

Elvis Mawodzeke

224198275

February 2026

**Abstract**

Efficient and spatially explicit quantification of water levels in small water bodies is vital for sustainable water resource management, particularly in arid and data-scarce regions. While satellite remote sensing provides regional-scale observations, its coarse spatial resolution limits applicability to small water bodies. Unmanned Aerial Vehicles (UAVs) bridge this gap by offering high-resolution, site-specific spatial and temporal changes. The first objective of this study was to systematically review UAV-based studies on water level mapping, assessing their progress, challenges, and opportunities. The reviewed literature shows that UAVs achieve accuracies up to $R^2 = 0.85$ relative to in situ and airborne data, utilising photogrammetry, LiDAR, and radar sensors-mostly integrated with DJI platforms. Advanced modelling techniques such as linear regression, convolutional neural networks, and support vector machine regression achieved mean RMSEs of 0.65 m, 0.035 m, and 0.39 m, respectively. Literature indicated a potential gap of UAV-derived data for mapping water levels in small water bodies. Hence, the second objective was to assess the spatial and temporal resolution capabilities of drones in detecting and mapping water levels in small water bodies. The DJI Matrice 300, equipped with a Mica Sense multispectral camera and a Zenmuse L1 LiDAR sensor, was used to monitor water level variations at High Down Stud Dam, Pietermaritzburg. Multispectral images were used to assess the changes in water surface extent through water spectral-based indexing, such as MNDWI. UAV LiDAR data enabled the precise quantification of water level fluctuations through elevation differencing between water surfaces and land boundaries. To address the limitations of using only UAV-derived data, water depth measurements obtained with a dipstick were used for validation. Rando Forest (RF) and Extreme Gradient Boosting (XGBoost) models were implemented to assess the predictive accuracy of the developed approach. The Random Forest (RF) model demonstrated strong predictive performance, achieving coefficients of determination ($R^2$) of 0.96 and 0.97 for May and October, respectively, with corresponding RMSE values of 0.12 m and 0.11 m, and relative RMSE (rRMSE) of 1.36% and 1.14%. Similarly, the XGBoost model performed well, attaining $R^2$ values of 0.95 and 0.96 in May and October, respectively, with RMSE values of 0.13 m for both months and rRMSE of 1.57% (May) and 1.39% (October). The study will contribute to a broader perspective of combining remote sensing techniques with in-situ validation and machine learning techniques in assessing the capabilities of drones in mapping water levels in small water bodies.

**Keywords**: Systematic review, Remote Sensing, GIS, UAVs, water levels, reservoir, spatiotemporal changes.

**Preface**

The research described in this thesis was carried out in the School of Environmental Sciences, University of KwaZulu-Natal, Pietermaritzburg, from February 2024 to December 2025, under the supervision of Prof. Onisimo Mutanga, Dr Tsitsi Bangira, Prof. Mbulisi Sibanda and Prof. Tafadzwanashe Mabhaudhi.

I confirm that the research reported in this thesis has never been submitted, in any form, to any other university or academic institution. It constitutes my original work, except where other sources have been cited and acknowledged.

Supervisors signature:

Prof. Onisimo Mutanga………[redacted]…………...Date: 28/01/2026

Co-supervisors: Dr. Tsitsi Bangira

Prof. Mbulisi Sibanda

Prof. Tafadzwanashe Mabhaudhi

**Plagiarism Declaration**

I, Elvis Mawodzeke, hereby declare that:

1. The research presented in this thesis, except where otherwise stated, constitutes my original work.
2. This work has not been submitted, either wholly or partially, for a degree or academic qualification at any other institution.
3. This thesis does not incorporate any data, figures, or content attributed to others, unless such material is clearly cited and acknowledged.
4. The thesis does not contain the written work of others, unless specifically acknowledged. Where such sources have been used, the text has been paraphrased, and the original ideas have been appropriately referenced.
5. This thesis does not include any text, graphics, or tables copied from Internet sources, except where such material has been acknowledged and properly cited both within the thesis and in the reference list.

Signed [redacted]_ Date: 28/01/2026

**Manuscripts Declaration**

1. Elvis Mawodzeke, Tsitsi Bangira, Mbulisi Sibanda, Onisimo Mutanga, and Tafadzwanashe Mabhaudhi. (2026). "Utility of UAV-borne sensors for detecting and mapping water levels in small water bodies: A systematic review of progress, challenges and opportunities." Remote Sensing Applications: Society and Environment 42:101973.
2. **2.** Mawodzeke, E, Bangira, T, Sibanda, M, Mutanga, O and Mabhaudhi, T (2026). Assessing the capabilities of UAVs in detecting and mapping water levels in small water bodies using machine learning techniques.

Signed [redacted]

## Dedication

*To my father, Norman Mawodzeke, you have always been my pillar of strength. I am profoundly grateful for your presence as a father figure.*

*To my mother, Venah Mawodzeke, I thank you so much.*

*To my brother Naboth T Mawodzeke, I thank you for supporting me from day one of my studies.*

**Acknowledgements**

I would like to thank God for good health and divine guidance.

The successful completion of this thesis would not have been possible without the generous support, guidance and assistance of numerous individuals and organisations.

My heartfelt gratitude is extended to my supervisor, Prof. Onisimo Mutanga, for his invaluable guidance and mentorship throughout this study. My deep gratitude and sincere appreciation are also extended to my co-supervisors, Dr Tsitsi Bangira, Prof. Mbulisi Sibanda and Prof. Tafadzwanashe Mabhaudhi. Your offices were always open for me; to discuss progress and any academic challenges that I would be facing. Without their guidance, expertise, and unwavering social, psychological and support, the completion of this work would not have been possible.

My special thanks also go to Dr Tinashe Kanosvamhira from the Department of Geography, Environmental Studies, and Tourism at the University of Western Cape for his unwavering support and encouragement. I would also like to express my sincere appreciation to Mr Celuxolo Dhlamini (PhD student, Department of Geography, University of KwaZulu-Natal) and Mr Bheka Mlambo (master's student, Department of Geography, University of KwaZulu-Natal) for their assistance during my fieldwork and for introducing me to Python. I deeply value their brotherly support, which has greatly enriched my academic journey, and I am truly grateful for their meaningful contributions.

I wish to express my sincere gratitude to Mr. Brice Gijsbertsen and Mr. Donavis de Vos of the Department of Geography, University of KwaZulu-Natal, for their consistent support in providing drones, equipment, and technical assistance for my fieldwork, your help is sincerely appreciated. My sincere appreciation also goes to my seniors, Ms Anita Masenyama, Dr Dadirai Matarira, and Dr Adeola. M. Arogoundade, for their steadfast guidance and encouragement.

My deepest gratitude goes to Andile Etah Mshengu for organising and coordinating all my fieldwork and logistics. Words cannot fully convey my appreciation. I am truly grateful for your invaluable support. I am deeply grateful to Mr Thulani Mnguni, Manager of the Umgenipoort Research Facility, for generously providing the boat and assisting with access to High Down Stud Farm Dam.

I extend my sincere thanks to Prof. John Odindi, Prof. Trevor Hill, and Mrs Shanita Ramroop for warmly welcoming me into the department, which made my research much easier. I extend my appreciation to the Water Research Commission of South Africa as part of project C2022/2023-00912, entitled "Assessing the utility of drone technology in monitoring water availability and quality in irrigation canals and dams for improving crop water productivity and enhancing precision agriculture in smallholder farms" and the National Research Foundation (NRF) Chair in Land Use Planning and Management-UKZN (Grant number 84157) for funding this research.

Lastly, I also wish to thank my entire family for their continuous moral support and constant encouragement, which have been invaluable throughout this journey.

**Table of Contents**

**Tables**



**Figures**

**Acronyms**

| | |
|---|---|
| AWEI | Automated Water Extraction Index |
| DEM | Digital Elevation Model |
| DJI M300 | Da-Jiang Innovations Matrice 300 |
| DSM | Digital Surface Model |
| FOV | Field of View |
| GCPs | Ground Control Points |
| GNSS | Global Navigation Satellite System |
| GPS | Global Positioning System |
| IMU | Inertial Measurement |
| LiDAR | Light Detection and Ranging |
| MNDWI | Modified Normalised Difference Water Index |
| NDVI | Normalised Difference Vegetation Index |
| NDWI | Normalised Difference Water Index |
| NIR | Near Infrared |
| PRISMA | Preferred Reporting Items for Systematic Reviews and Meta-Analysis |
| QGIS | Quantum Geographic Information System |
| $R^2$ | Coefficient of Determination |
| RF | Random Forest |
| RGB | Red, Green, Blue |
| SAGA | System for Automated Geoscientific Analyses |
| SONAR | Sound Navigation and Ranging |
| UAVs | Unmanned Aerial Vehicles |
| WSE | Water Surface Elevation |
| XGBoost | Extreme Gradient Boosting |

## Chapter One

### 1.1 General introduction

The global water resources are unevenly distributed, both temporally and spatially. Approximately 97.5% of the planet's water is salt, while only about 2.5% is freshwater (Bandini, 2017). Moreover, most of this freshwater is stored as ice, snow, groundwater, and soil moisture, with nearly 0.3% existing as surface water in liquid form. Of the small fraction of liquid freshwater found at the Earth's surface, approximately 87% is stored in lakes, about 11% occurs in wetlands, and only around 2% is found in rivers (Bandini, 2017; Bandini et al., 2020; Woolway et al., 2020). Over recent decades, increasing evidence has revealed substantial spatiotemporal variability in lake water levels, primarily attributed to climate variability and intensifying anthropogenic pressures such as land-use change, water abstraction, and reservoir or small water body or dam (used interchangeably) regulation (Kasvi et al., 2019; Legleiter & Harrison, 2018). In this context, accurate mapping and monitoring of small water bodies have become increasingly important for effective water resources management. Such monitoring supports water and land-use planning, promotes sustainable resource management, enhances flood detection and mitigation, and contributes to the conservation of aquatic ecosystems (Barros et al., 2025).

Since 1980, global demand for freshwater has increased steadily at an average rate of approximately 1% per year, driven primarily by population growth and socioeconomic development (Messager et al., 2016; Woolway et al., 2020; Yigzaw et al., 2018). Sustainable management of small water bodies therefore, depends on a comprehensive understanding of the complex and interconnected processes influencing both water quantity and quality, which underpin human consumption, economic development, and ecosystem functioning (Szostak et al., 2023). Accurate observation of key hydrological variables such as surface water extent, water levels, and their spatiotemporal variations enhances the quantitative understanding of hydrological processes and strengthens the precision and reliability of hydrological predictions (Bandini, et al., 2017).

A range of approaches has been developed to characterise water-level dynamics in small water bodies across spatial and temporal scales, including field observations, and measurements (Blöschl et al., 2019; Cho & Qi, 2025; Dwivedi et al., 2025). However, conventional surface water management has traditionally relied on in situ hydrometric gauge networks. Although these point-based measurements offer high local accuracy, they offer limited spatial representativeness and are often insufficient for fully characterising small, heterogeneous reservoirs and dams. Furthermore, a global decline in hydrometric monitoring networks is increasingly apparent, with many developing regions exhibiting sparse or non-existent gauge coverage (Lawford et al., 2013; Massuel et al., 2022).

Remote sensing methods offer an effective solution for addressing these data gaps by providing spatially explicit, repeatable, and synoptic observations of surface-water dynamics (Acharya et al., 2021; Bandini et al., 2020; La Salandra et al., 2025). Although no universally accepted definition of a small reservoir exists, such systems are commonly classified as having surface areas ranging from 0.01 $km^2$ to 1 $km^2$ (Biggs et al., 2017). Meanwhile, small rivers are defined as flowing water bodies with a width of less than 30 m and a catchment area smaller than 100 $km^2$ (Backes et al., 2020; Kinzel & Legleiter, 2019). Small reservoirs and rivers are collectively considered small water bodies. Monitoring these small water bodies remains challenging, as the spatial resolution of freely available satellite imagery is often insufficient. Landsat provides 30 m resolution, while Sentinel-2 offers 10 m resolution with revisit intervals of up to two weeks (Binh & Son, 2021).

In this regard, unmanned aerial vehicle (UAV)–based measurement techniques present considerable advantages, providing high spatial-resolution, flexible temporal sampling, rapid deployment, and the ability to collect data in remote or inaccessible areas (Giulietti et al., 2022; Liu et al., 2025; Vélez-Nicolás et al., 2021). Unmanned aerial vehicles (UAVs) leverage advancements in automation, sensor technologies, and image processing to acquire real-time data, thereby enhancing spatial and temporal resolution. Overall, this improves time effectiveness and accuracy in the assessment of water levels in small water bodies (Acharya et al., 2021; Woodget et al., 2017).

Several UAV-borne sensors are being used to map water levels, including RGB Witek et al. (2025), multispectral sensors Wang et al. (2025), Sonar, Light Detection and Ranging (LiDAR) and Radar (Hu et al., 2025; Zhou et al., 2025b). The use of multispectral UAV technology, with its enhanced spatial resolution, enables the rapid generation of high-detail water extent maps and allows flexible planning and adjustment of data acquisition parameters according to survey conditions (Gafurov et al., 2024; Gafurov et al., 2021; Liu et al., 2025). UAV LiDAR-derived data enables the accurate derivation of water surface elevation (WSE) models, which are of paramount importance in determining the quantity of water in small reservoirs. Sonar and radar sensors onboard UAVs can effectively provide water levels and depth in small water bodies.

For instance, Bandini, et al. (2018b) reported that sonar-based water surface elevation (WSE) measurements achieved an accuracy within 5–7 cm, while radar water depth estimates attained an accuracy of approximately 3.8% of the actual depth in cenotes and lagoons of the Yucatán Peninsula, Mexico. Bandini et al. (2020) compared water surface elevation using radar, LiDAR and photogrammetry in Åmose Å and Nivå Å small streams in Denmark. Subsequently, the technique of using LiDAR attained a RMSE of 0.016 m, proving to be robust. In comparison, radar and photogrammetry-based methods yielded higher RMSE values of 0.022 m and 0.03 m, respectively. Meanwhile, radar-based resolution offers the advantage of shorter data acquisition and processing times.

However, photogrammetry typically demands substantial computational resources and involves time-intensive manual identification of ground control points (GCPs) and visual inspection of water-edge features (Massuel et al., 2022). Meanwhile, LiDAR data requires advanced calibration and filtering to separate water surface, bottom returns, and filter outliers (Hu et al., 2025). However, LiDAR remains one of the most effective and widely adopted technologies for acquiring high resolution topographic data, particularly in regions where ground-based observations are limited or unavailable. Its ability to capture detailed water surface characteristics over large and inaccessible areas makes it especially suited for this study. While certain challenges including processing complexities, poor performance in turbid waters, vegetation interference and data calibration exist, they highlight the importance of appropriate processing and methodological choices, which are addressed in this study.

Other than optimal remotely sensed data, numerous machine learning approaches have been utilised in predicting water surface extent, and water levels in complex water bodies. These encompass Support Vector Machines (SVM) Agrafiotis et al. (2019), Artificial Neural Networks (ANN) Kim et al. (2019); deep and shallow Neural Networks (DNNs) He et al. (2022); Random Forest (RF) Gafurov et al. (2024); Extreme Gradient Boosting (XGBoost) Liu et al. (2025a). Machine learning techniques yield inversion results that are closely aligned with ground-measured data. Hence, the need to assess the capability of UAV-borne sensors to detect and map water levels in small water bodies by evaluating sensor performance, modelling approaches, and quantitative accuracy metrics. Although machine-learning models have demonstrated promising results, few studies have rigorously examined their predictive ability when applied specifically to UAV-derived multispectral and elevation datasets in small reservoir environments. Therefore, this study sought to assess the capability of UAV-borne multispectral and LiDAR sensors for mapping water levels in small water bodies.

## 1. 2 Aim and objectives

This study aimed to assess the capabilities of drone remote sensing in mapping water levels in small water bodies. To achieve this, the following specific objectives were set:

1. To systematically review and synthesize existing literature on the feasibility of UAV-derived remote sensing data in detecting and mapping water levels in rivers and dams.
2. To assess the capability of integration of UAV-borne sensors with machine-learning in detecting and mapping seasonal water levels and surface extent in small water bodies.

## 1.3 Thesis outline

This work consists of two journal papers submitted to international journals in the fields of geographic information systems and remote sensing applications for peer review. One of these journal papers have been published online and the other one is currently under review. Each paper is presented as an individual chapter, specifically designed to address the overall aim of this study. The original content and format of the peer-reviewed article was maintained in the compilation of this thesis. Each chapter includes an introduction and conclusion that connect to the next, resulting in some overlap of hypothetical content due to the continuous flow of fundamental principles continue to flow. These repetitions are minimal and acceptable, since the other paper was peer-reviewed by international journal and each paper can stand independently without compromising the overall coherence of the thesis.

# Chapter Two

**Utility of UAV-borne sensors for detecting and mapping water levels in small water bodies: A systematic review of progress, opportunities and challenges**

This chapter is based on:

Remote Sensing Applications: Society and Environment 42 (2026) 101973

Contents lists available at ScienceDirect

ELSEVIER

Remote Sensing Applications: Society and Environment

journal homepage: www.elsevier.com/locate/rsase

Utility of UAV-borne sensors for detecting and mapping water levels in small water bodies: A systematic review of progress, opportunities and challenges

Elvis Mawodzeke [a,*], Tsitsi Bangira [b], Mbulisi Sibanda [c], Onisimo Mutanga [d], Tafadzwanashe Mabhaudhi [a,b,e]

[a] *Centre for Water Resources Research, School of Agricultural, Earth and Environmental Sciences, University of KwaZulu-Natal (UKZN), Scottsville, Pietermaritzburg, South Africa*

Elvis Mawodzeke, Tsitsi Bangira, Mbulisi Sibanda, Onisimo Mutanga, and Tafadzwanashe Mabhaudhi. (2026). “Utility of UAV-borne sensors for detecting and mapping water levels in small water bodies: A systematic review of progress, challenges and opportunities.” Remote Sensing Applications: Society and Environment 42:101973.

**Abstract**

Efficient and spatially explicit quantification of water levels in small reservoirs is critical for managing scarce water resources, particularly in arid developing regions. While satellite remote sensing has been widely used at regional scales, its coarse spatial resolution limits applicability for small rivers and reservoirs. Unmanned aerial vehicles (UAVs) bridge this gap by providing high-resolution and site-specific observations. This study systematically reviews the use of UAV-derived data in mapping water levels in small water bodies. Most studies use photogrammetry, LiDAR, or radar on DJI platforms. Reviewed studies showed that K-nearest neighbours, convolutional neural networks, and support vector machine regression models optimally estimated water levels to average RMSEs of 0.039 m, 0.35 m and 0.59 m, respectively. Image differencing and empirical model-based enhancement were the most applied processing techniques in the reviewed literature. Despite these advances, progress remains constrained by limited research and the lack of robust water quantity datasets for model parameterization.

**Keywords**: UAVs, remote sensing, water levels, bathymetry, rivers, reservoirs.

## 2.1. Introduction

Freshwater accounts for only 2.5% of the total amount of water on the Earth`s surface, and only 1.5% of that amount is accessible for biophysical processes(Stephens et al., 2020). Global freshwater withdrawals and usage have risen nearly sixfold since 2024, with approximately 70% used in agriculture, 20% in industries, and 12% for domestic or municipal purposes (Canton, 2021; Hirji & Duda, 2025; Ritchie et al., 2018). About 70% of the total freshwater usage is mostly for irrigation purposes (Canton, 2021; Finley & Seiber, 2014). Consequently, global agricultural production is expected to increase by 60 to 70%, which will substantially increase water demand (Gholizadeh et al., 2016). Meanwhile, the intensifying competition for water resources across sectors is projected to escalate significantly as the global population rises from the current 7.8 billion to about 9.7 billion by 2050 (Mishra et al., 2023). This looming water scarcity crisis necessitates the urgent need for robust and effective water management practices. A critical component of these practices is the ability to conduct accurate, time and cost-effective assessments of water availability. Such assessments are particularly vital in arid and semi-arid regions, where agricultural productivity depends heavily on small water bodies that are especially vulnerable to climatic and anthropogenic pressures (Massuel et al., 2022).

In developing regions, including Southern Africa, water resources are unevenly distributed, and this is compounded by climate variability, particularly the unpredictable seasonality of precipitation (Bangira et al., 2015; Sibanda et al., 2021). In this regard, there is an urgent need to identify accurate and efficient methods for assessing the quantity of available surface water resources for their sustainable management (Gholizadeh et al., 2016). The quantity of available water resources is conventionally determined from in-situ measurements, which in some cases can be time-consuming and costly (Acharya et al., 2021; Liu et al., 2025). This information may not be readily available to users such as farmers who urgently require it for managing the irrigation water resources (Gholizadeh et al., 2016; Kaya et al., 2023).

Conventional water level techniques, commonly employed in small water bodies, include staff gauges, float-operated devices, and pressure transducers. Staff gauges, consisting of graduated boards fixed vertically along riverbanks, lake shores, or reservoir walls, allow for straight forward visual observation of water levels. Float operated devices measure changes in water levels by recording the rise and fall of a float, which is then transmitted through mechanical or electronic systems for interpretation. Pressure transducers record the hydrostatic pressure exerted by water, allowing precise measurement of depth (bathymetry) in small water bodies. For instance, they actively monitor temporal variations in water level at Roodeplaat Dam, South Africa, to assess reservoir dynamics (Singh, 2023). However, these techniques, are time-consuming, and inadequate for spatial and temporal assessments. Alternatively, earth observation facilities have emerged and have been demonstrated to be a suitable alternative source of spatially explicit data applicable in time-effectively detecting and measuring reservoir water quantity (Carballido, 2023; Duan et al., 2021; Li et al., 2022). Literature indicates that satellite-borne sensors offer data with optimal resolutions for mapping water levels in different reservoirs at regional scales (Acharya et al., 2021). However, the spatial and temporal inflexibility of these platforms precludes the possibility of on-demand data acquisition that is often necessary to capture the highly transient processes operating at fine spatial scales of water reservoirs.

Recent advances in remote sensing sensors, image processing tools and techniques, have seen the emergence of sensors on board unmanned aerial vehicles (UAVs), also known as unmanned/unoccupied aerial systems (UAS) or drones (Jiang et al., 2022). Drones offer an optimal, rapid, accurate and cost-effective approach to acquiring remotely sensed data on a demand basis for spatially quantifying and understanding water quantity in complex settings at a finer spatial resolution (Bandini et al., 2020; Jiang et al., 2020; Zhou et al., 2025b).

Monitoring spatial and temporal water levels in small water bodies is of paramount importance for flooding and drought monitoring. Drones are one of the technology-oriented platforms which could significantly assist in monitoring water levels and improve flood prediction (Barros et al., 2025; Liu et al., 2025). This is because drones are flexible and relatively have high spatial and temporal resolution in comparison to space-borne remote sensing and field-based approaches. While field-based measurements are often labour-intensive, localised, and constrained by accessibility, drones can cover complex and remote reservoirs efficiently, including hazardous zones that pose a risk to human safety. Their capacity to integrate diverse sensors, such as RGB, multispectral, and LiDAR, further enhances their ability to generate detailed water depths and surface extent. Drones can be flown at low altitudes, offering very high spatial resolution data, with high prospects for timely and accurate characterisation of water levels in rivers and dams (Bandini, et al., 2017; Bandini et al., 2023; Yang, et al., 2019a). For instance, Ridolfi and Manciola (2018) measured water levels of the medium-sized Ridracoli Dam, located in the Emilia-Romagna Region of central Italy, which extends approximately 5km using a UAV. Ridolfi and Manciola (2018) findings reveal that the estimated water levels deviate from the true values by an average of only 0.05m. Zhou et al. (2025b) conducted UAS-based hydrometric surveys along a stretch of 10 km of the Rönne Å River in Sweden, capturing contactless measurements of river water level, bathymetry, and flow velocity. Recent advances in oriented synthetic aperture radar (SAR) ship detection, particularly those integrating edge-aware deformable convolution and point set representation with UAV-derived data, have demonstrated robust performance in mapping water levels in small water bodies (Li et al., 2024). For example, Guan et al. (2025) applied an edge-aware framework combining deformable convolution networks and radial basis function–based point set transformation to accurately characterise irregular and discontinuous geometries in SAR imagery, thereby improving boundary delineation and enhancing the precision of water level estimation.

Despite the successful application of UAVs in mapping water quantity in reservoirs, there remains an urgent need for a comprehensive understanding of the progress, challenges and gaps associated with utilising UAV-acquired data for mapping water levels, particularly in the Global South. This is very critical for advancing methodologies for mapping water levels, addressing existing gaps and improving decision-making. Hence, fostering cross-disciplinary collaborations geared towards supporting the sustainable use of already-stressed water resources, in the face of climate change and variability, through integrated monitoring, adaptive management strategies, and evidence-based policy development.

Meanwhile, approximately five studies sought to review the literature on the utility of UAVs in acquiring remotely sensed data on water levels in small open water bodies. For instance, Acharya et al. (2021) analysed UAV applications in hydrology and water management, addressing water level monitoring, bathymetry, and flood assessment. Vélez-Nicolás et al. (2021) assessed UAV applications in surface and groundwater studies, identifying commonly used platforms, sensor configurations, derived products, and research gaps. Sibanda et al. (2021) explored UAV applications in mapping and modelling open water resources, focusing on water quality and quantity. Mishra et al. (2023) reviewed UAV technologies for water resource monitoring, focusing on sensor systems, processing software, and operational constraints. Pizarro et al. (2024) evaluated UAV-based river monitoring, with emphasis on morphological dynamics and water-level variability.

However, these studies did not focus on assessing the utility of UAVs in remote sensing dynamics of water levels in small rivers and dams. In this study, small water bodies are natural or artificial water surface features such as lakes, or reservoirs <10km$^2$, ponds, small canals, seasonal floodplains, and streams or rivers <50km (Bauer-Gottwein et al., 2024; Carballido, 2023; Duan et al., 2021; Zhou et al., 2023). This study aims to review and critically assess the existing literature on the utility of UAV-acquired remotely sensed data for detecting and mapping water levels of rivers and dams. It also seeks to explore the progress, challenges and opportunities associated with the use of UAVs in monitoring water levels in open water reservoirs. By doing so, the study contributes to the broader discourse supporting the United Nations Sustainable Development Goals (SDGs), particularly SDG 2, which focuses on ending hunger, achieve food security, improving nutrition and promote sustainable agriculture through enhanced irrigation and SDG 13, which underscores the urgent need to address the impacts of climate change on water resources (Briggs, 2018; Ho & Goethals, 2019).

### 2.2. Materials and Methods

The Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) approach (https://www.prisma-statement.org/, retrieved on 03 March 2025) and checklist were utilised in addressing the aims of the study (Page et al., 2021). This systematic writing assessment is arranged in two main sections. The first section aims to assess the improvement reached in monitoring water levels in small reservoirs and identifying existing research gaps.

The second section focuses on outlining and discussing the key challenges and emerging opportunities associated with the utility of UAVs technologies in mapping and measuring water levels in rivers and dams. To address these objectives, the literature search and analysis were conducted in three distinct phases

**2.2.1. Literature search**

Inclusion and exclusion search criteria were defined to describe the aim of the study. Questions were formulated regarding the use UAVs for water-level monitoring, mapping, and detection. These were as follows:

- What literature exists on the usage of UAVs for mapping water levels in rivers and dams?
- Which drone platforms and associated sensor technologies have been increasingly used for monitoring water levels in rivers and dams?
- What is the reported accuracy of UAV sensors in literature?
- Which techniques and spectral transformation methods have been effectively used to map water levels in rivers and dams?
- What challenges, gaps and opportunities are associated with monitoring water levels in rivers and dams using UAV-borne sensors?

The preliminary phase of the literature search was to select keywords, terms, and phrases relevant to the study. The research topic was copied and pasted into Web of Science to identify keywords, terms and phrases. The four most recent articles (Acharya et al., 2021; Mishra et al., 2023; Sibanda et al., 2021; Vélez-Nicolás et al., 2021)-were reviewed to extract keywords. Drawing on these sources and the study's research questions; a final set of keywords was compiled to construct a search query. This query was subsequently utilised for a comprehensive literature search across Scopus, Web of Science, PubMed, and Google Scholar (Table 2.1) for the period 2000-September 2025. The selected time frame captures the evolution of UAV technology and its applications in water level mapping, including recent advancements before the cut-off date (Vélez-Nicolás et al., 2021). Specifically, the following keywords were used: "unmanned aerial vehicle(s)", "drone(s)", "remote sensing", "GIS", "water levels", "water surface elevation", "river(s)", "water bodies", "dam(s)", "reservoir(s)" OR "water quantity", and "water volume". During the search process, the query string was adjusted as needed to fit the criteria of each search platform (Table 2.1). The search terms were carefully tailored to each database's indexing system to maximise retrieval accuracy while minimising irrelevant results. This process yielded 1106 records.

Table 2.1. Key words search.

| Search platform | Search criterion | Direct hits of articles | Retained articles |
|---|---|---|---|
| Scopus | TITLE-ABS-KEY(("Unmanned aerial vehicle" OR "UAV*" OR "UAS" OR "drones" ("flood*" OR "flood detection") ("water bodies" OR "dam*" OR "basin*" OR "reservoir*" OR "River*") W/10 ("water*" OR "water quantity" OR "water level*" OR "water surface elevation") AND NOT ("groundwater" OR "underground water" OR "coastal waters" OR "seawater")) AND PUBYEAR > 1999 AND PUBYEAR < 2025 AND ( LIMIT-TO ( LANGUAGE, "English" )) AND ( LIMIT-TO DOCTYPE, "ar")) | 276 | 191 |
| Web of science | TS= (("Unmanned aerial vehicle" OR "UAV*" OR "UAS*" OR "drone**" OR "Remote sensing*" OR "GIS") AND ("flood*" OR "flood detection) ("water bodies*" OR "dam*" OR "basin" * OR "reservoir*" OR "River*") AND ("water quantity" OR "water levels" OR "water surface elevation" OR "water volume") NOT ("groundwater" OR "underground water" "coastal water" OR "estuaries")) | 267 | 205 |
| PubMed | (("unmanned aerial vehicle*" OR "UAV" OR "UAS" OR "drone*" OR "remote sensing" OR "GIS") AND ("river*" OR "Dam" OR "basin*" OR "reservoir*" OR "water bodies*" OR "open water source*") AND ("water quantity" OR "water volume" OR "water level*" NOT ("groundwater" "coastal water" OR "estuaries" "wetland*")) | 174 | 79 |
| Google scholar | ("unmanned aerial vehicle" OR "UAV*" OR "UAS" OR "drone*" OR "remote sensing" OR "GIS") AND ("river*" OR "Dam*) AND ("water quantity" OR "water volume" OR "water surface elevation" AND ("water levels sensor*" OR "UAV sensor*") AND ("feasibility" OR "viability") NOT ("groundwater water" "coastal water" OR "estuaries") | 389 | 268 |
| | Articles considered before screening after removing duplicates | 1106 | 743 |
| | Articles on UAV application in water levels | | 110 |

TS, topic; TITLE-ABS-KEY; title, abstract, and keywords; DOCTYPE, 'ar' = document type 'article'; W/10= is a proximity operator which specifies that two search terms must be within ten words from each other, regardless of the order of the words.

### 2.2.2. Selection criteria

The screening process followed the PRISMA guidelines (Figure 2.1). In the identification stage, 363 duplicate records were removed, leaving 743 records. In the screening stage, 341 records were identified as potentially eligible. Excluded from the review were non-English publications (n = 38), items unavailable in PDF format (n = 41), and records not classified as journal articles or inaccessible in full text (n = 323). Title and abstract screening then removed 242 additional records focusing on coastal waters, estuaries, celestial bodies, or topics outside the study scope (Figure 2.1).

After these exclusions, 99 full-text articles remained for eligibility assessment, with a further 11 studies identified through backward referencing (Horsley et al., 2011), all of which underwent full-text assessment for eligibility (Figure 2.1). In total, 110 articles met the selection criteria and were carried out for data extraction. The selection procedure and screening results are illustrated in a PRISMA flow statement (Figure 2.1).

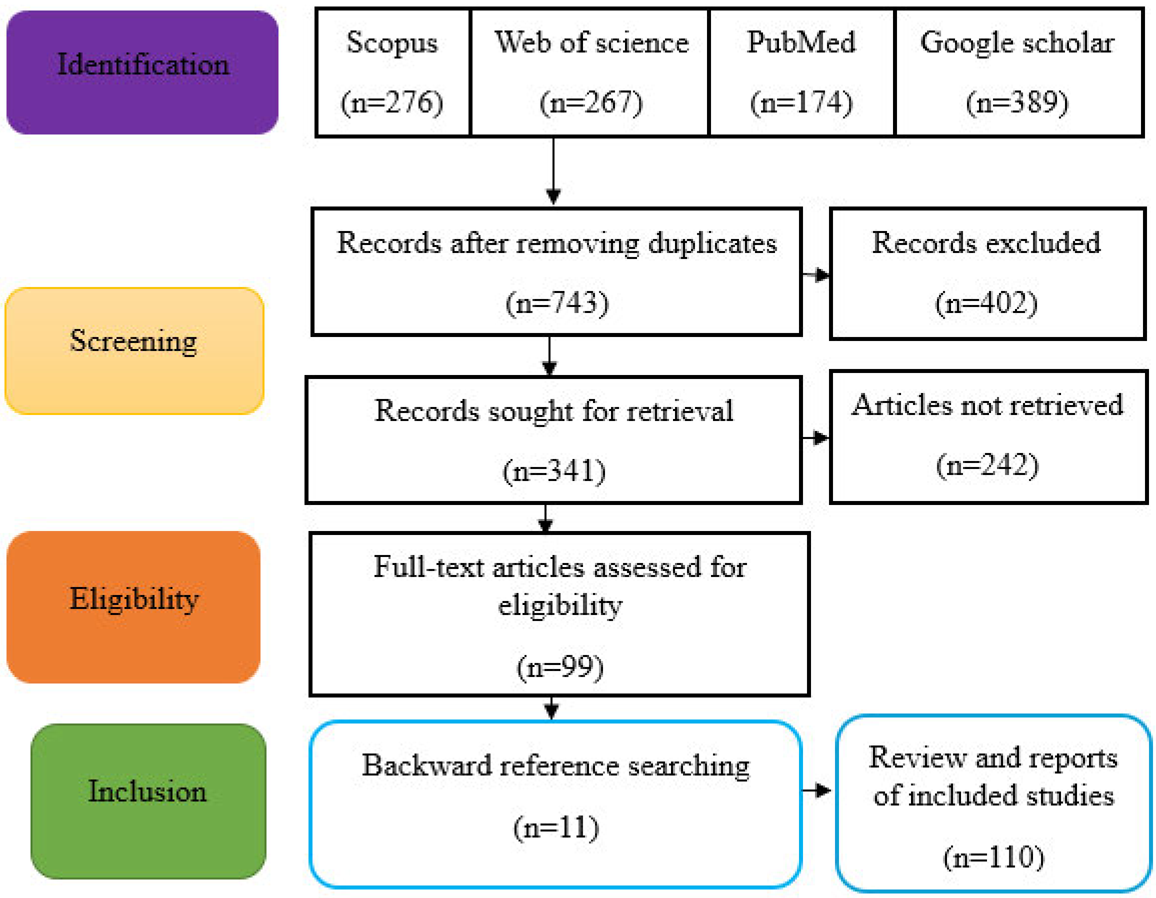



Figure 2.1. Prisma flow statement demonstrating article selection procedures.

### 2.2.3. Data extraction

Data from eligible articles were exported from EndNote into an Excel spreadsheet, including key bibliographic fields: author, publication year, article tittle, journal name, keywords, abstract, and digital object identifier (DOI). The coefficient of determination ($R^2$), also known as the goodness-of-fit metric as well as root mean square error (RMSE), were used to compare the performance of different models. This scaled accuracy parameter quantifies the magnitude of association between predicted and measured water levels variables (Cameron & Windmeijer, 1997; Chicco et al., 2021). Additionally, the frequency of articles was analysed to assess the prevalence and importance of the research topic and contributing authors. These frequency data, expressed as counts and percentages, were used to identify research trends, gaps, and areas of concentrated activity, supporting the synthesis and critical evaluation of existing literature.

### 2.2.4 Data Analysis

In the third and final stage, the exported data were analysed both qualitatively and quantitatively. Graphical presentations were generated to illustrate key findings. Bibliometric analysis was conducted to assess and visualize occurrence and co-occurrence trends of key terms extracted from titles and abstracts of the retrieved literature. Evolutionary trends were analysed using VOSviewer software (https://www.vosviewer.com/) by statistically evaluating the occurrence and co-occurrence of key terms in the tittles and abstracts of the reviewed literature (Van Eck & Waltman, 2010). A total of 478 keywords were recognised in VOSviewer Software from the reviewed literature. To study the trends, the lowest number of occurrences was set to seven, which narrowed down to a threshold total of 37 keywords. In assessing the progress in the utilization of UAV-acquired remotely sensed data in mapping water levels, basic statistical frequencies and tests of significant variation in $R^2$ and RMSE were captured.

## 2.3. Results

### 2.3.1. Evolution and analysis of keywords in UAV-derived water levels literature

In analysing the literature characteristics of the retrieved studies, the network map (Figure 2.2), categorized the identified literature into six clusters of concepts. The red cluster had "light detection and ranging," "river discharge," "synthetic aperture radar," "unmanned aerial vehicles," "UAV," "rivers," "three-dimensional modelling," "hydrodynamics," "mean square error," "water surface elevations," and "gnss, " as its key terms. This cluster highlights the integration of sensor technologies, particularly lidar and synthetic aperture radar, with UAV platforms to enhance the efficiency and accuracy of surface water monitoring. The blue and purple clusters had their key terms as "water resources," "image analysis," " water level," "unmanned aerial vehicles," "rainfall," "reservoir," and "water levels, " indicating research that emphasises discharge estimation and the use of water surface elevation as a proxy for flooding and reservoir water levels.

The green cluster comprised “unmanned aerial devices,” “remote sensing,” “image enhancement,” “aerial vehicle,” “deep learning,” “hyperspectral,” and “uav remote sensing” as its key terms. These terms underscore the integration of UAV platforms, advanced sensing technologies, image preprocessing, and machine learning approaches that drive methodological innovation in high-precision water level mapping of small water bodies. The yellow cluster connected terms such as “precipitation,” “lakes,” and “gis,” reflecting the role of hydro-climatic drivers and geospatial analytical tools that contextualize UAV-based water level estimation within broader hydrological and environmental monitoring frameworks. Lastly, the purple cluster had key terms as “floods " and “dsm,” demonstrating the role of UAVs in flood detection, monitoring of inundated areas and quantifying water levels in open water bodies.

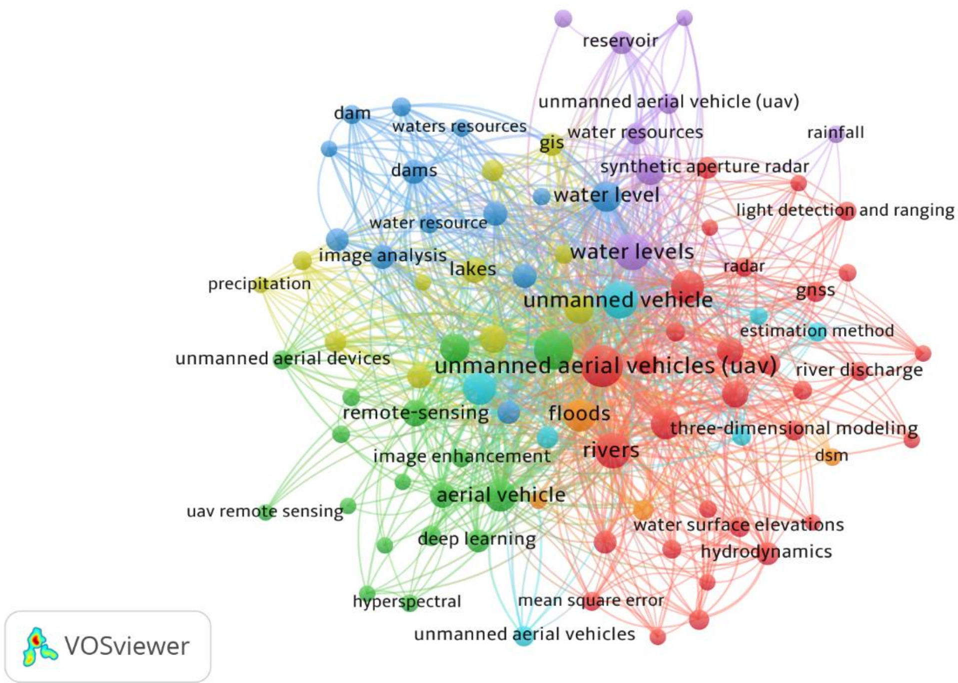



Figure 2.2. Topical concepts in water level mapping in rivers and dams.

The temporal evolution of topical concepts highlights the progressive development of UAV-based remote sensing applications in detecting and mapping water levels in rivers and dams. Specifically, in 2019 and 2020, dominant keywords included “water levels”, “dam”, “water resources” and “water surface elevations”, Figure 2.3, reflecting a widespread increase in the concept of remote sensing of water levels in rivers and dams. Between 2021 and 2022, the emergence of terms such as “rivers”, “floods”, “precipitation”, “uav remote sensing” and "image enhancement" indicated a shift toward event-driven hydrological monitoring and methodological refinement, emphasizing high-resolution UAV data integration and improved shoreline extraction for more accurate water level estimation in small water bodies. Between 2023 and 2024, the prevalence of keywords such as "hyperspectral", "unmanned aerial vehicles", "synthetic aperture radar", "deep learning", "river discharge", and "remote sensing" was noted (Figure 2.3). This reflects a shift toward advanced multi-sensor integration and AI-driven modelling, emphasizing high-precision water surface elevation retrieval, discharge estimation, and enhanced spectral–radar fusion for improved water level monitoring in rivers and dams.

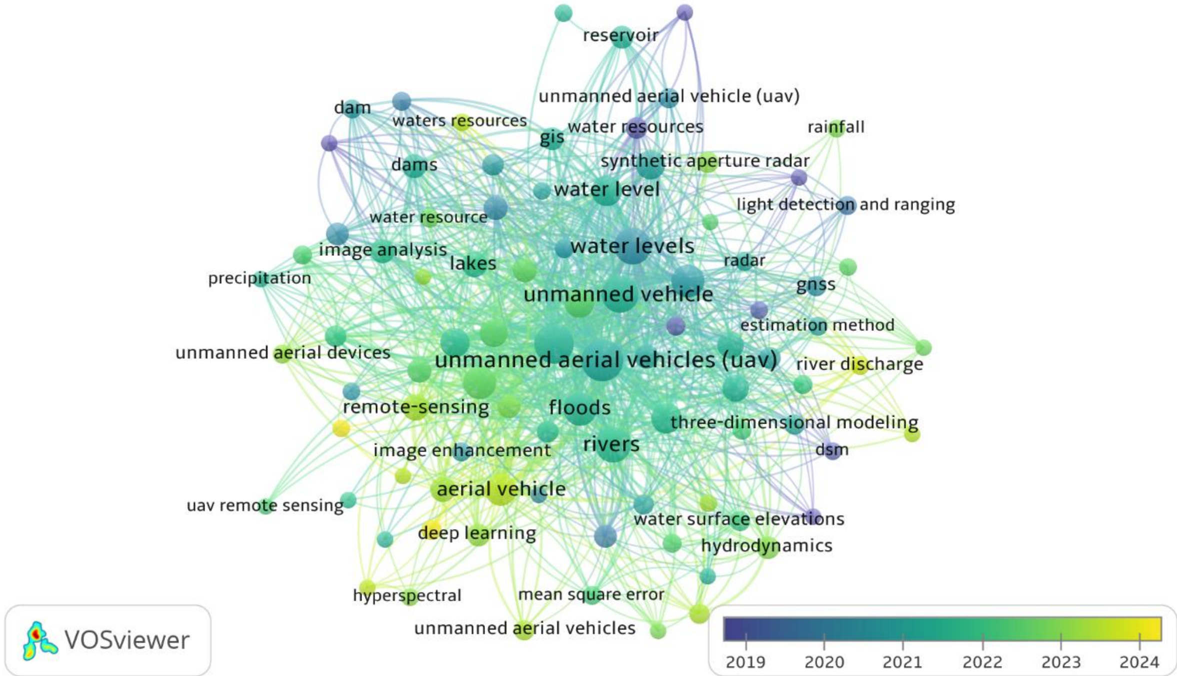



Figure 2.3. Evolution and direction of topical concepts on water levels mapping in rivers and dams using UAVs, derived from abstracts, titles and keywords of the selected literature.

### 2.3.2. Spatial and temporal distribution of publications

The use of UAV-acquired remotely sensed data for mapping water levels in rivers and dams emerged around 2007, marking the beginning of research exploring the potential of UAVs for high-resolution monitoring of small water bodies (Figure 2.4). Between 2012 and 2016, the adoption of UAVs in water levels mapping remained limited due to regulatory restrictions (Flener et al., 2013; Mandlburger et al., 2015; Zinke & Flener, 2013) (Figure 2.4). Studies during this period nonetheless provided detailed insights into river water level dynamics and geomorphological processes across different fluvial systems. Two contrasting yet illustrative examples include the Pulmanki River in Finnish Lapland and the Ain River flowing from the Jura Mountains, each demonstrating unique responses to seasonal variations, resulting in both spatial and temporal changes in water levels (Mandlburger et al., 2015).

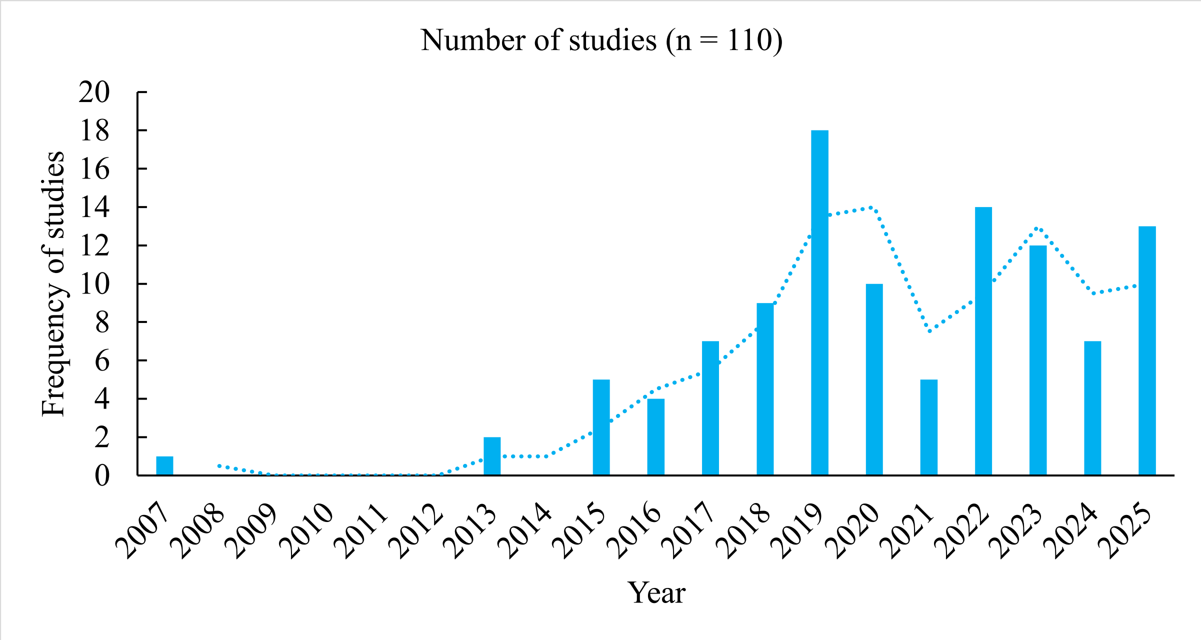



Figure 2.4. The trends of studies that utilised drone remotely sensed data to assess water levels in rivers and dams.

A notable increase in research activity was observed from 2017 onwards, accounting for approximately 18% of the reviewed studies, focusing on rivers, lakes and reservoirs (Langhammer et al., 2017; Mourato et al., 2017; Pai et al., 2017). This was largely driven by the easing of regulatory restrictions on the use of UAVs, which has enhanced accessibility and facilitated wider adoption of the technology in research.

An increase in research articles was observed between 2018 and 2019 (Figure 2.4). Gao et al. (2019), determined water levels and flood extent of Miaowei (reservoirs) on the Lancang River, Yunnan Province, China. Meanwhile, Bandini, et al. (2018) conducted water levels mapping in constantly stable sections of Fureso Lake, Amose A River and Marrebaek Canal in Denmark with limited vegetation. From 2019 onwards, the adoption of UAVs and the integration of LiDAR sensors for mapping water levels in dams and rivers increased markedly, reaching a peak in popularity (Figure 2.3, Figure 2.4). This period saw the intensification of both river and reservoir water levels mapping. For instance, Giulietti et al. (2022) assessed water levels of the Piave River, in the province of Belluno, Italy. Between 2022 and 2025, reviewed studies showed a marked intensification of data fusion approaches, alongside a growing adoption of deep learning and artificial intelligence techniques in UAV-based analyses.

In terms of the spatial distribution, the retrieved studies were conducted across thirty-eight different countries, with 49.56% in Europe, 30.43% in Asia, 10.43% in North America, 2.61% in South America, 0.87% in Oceania, 0.87% in the Middle East and 5.22% in Africa (Figure 2.5). In Asia, most of the studies were conducted in the Republic of China 19.13%, followed by Turkey 2.61% and the remaining 8.69 % in Taiwan, North Korea, South Korea, Singapore, Indonesia, Japan and Malaysia (Figure 2.5). In North America, 10.43% of the studies were done in the United States of America (USA) and Canada. Meanwhile, in North Europe had 18.26%, with Denmark occupying 11.3%, Sweden, United Kingdom, Finland and Norway 6.96% of the reviewed literature within the context of water level mapping in rivers and dams (Figure 2.4). Southern Europe accounted for 14.78% of the reviewed studies, with Italy contributing 6.09% and Austria 5.22%, while the remaining 3.47% were conducted in Switzerland, Spain, and Greece. In Central Europe, 10.43% of the reviewed studies were conducted in Poland and the Czech Republic. Meanwhile, in Western Europe, 4.35% of the reviewed studies were conducted in Germany, France, and Luxembourg (Figure 2.5). In Eastern Europe, Russia accounted for 1.74% of the reviewed studies investigating river and dam water levels using UAV-derived data. In Oceania, Australia accounted for 0.87% of the reviewed literature, while in the Middle East, Iran contributed 0.87%. In Africa, 5.22% of the reviewed literature were conducted in global south states including South Africa, Malawi, Botswana, Tanzania and Burkina Faso (Figure 2.5). The excessive number of studies in Europe can be ascribed to numerous factors. For instance, Europe has diverse water bodies, including numerous large rivers, lakes and reservoirs, providing diverse opportunities for water levels mapping in small water bodies research using UAV technology (Kujawa et al., 2025; Templin et al., 2018). Additionally, Europe has invested heavily in advanced UAV technology and remote sensing research, leading to more studies (Zhou et al., 2025b). The few studies in other regions could be due to less availability of advanced UAV remote sensing technologies and limited research funding (Hardy et al., 2017).

Approximately 35% of the reviewed studies examined water levels across both dry and wet seasons, whereas the remaining 65% addressed temporal variability by restricting data collection to individual seasons such as the summer, autumn, winter or spring. This distribution likely reflects practical limitations, including restricted research funding, compressed project timelines, and the seasonal framing of many research grants (Francis et al., 2022; Iqbal et al., 2023; Lee et al., 2019). Multi-season investigations, however, offer a distinct advantage, as they provide a more holistic understanding of hydrological variability and facilitate the identification of seasonal patterns and long-term trends in water availability (Ben Moshe & Lensky, 2024; He et al., 2023; Liu et al., 2022).

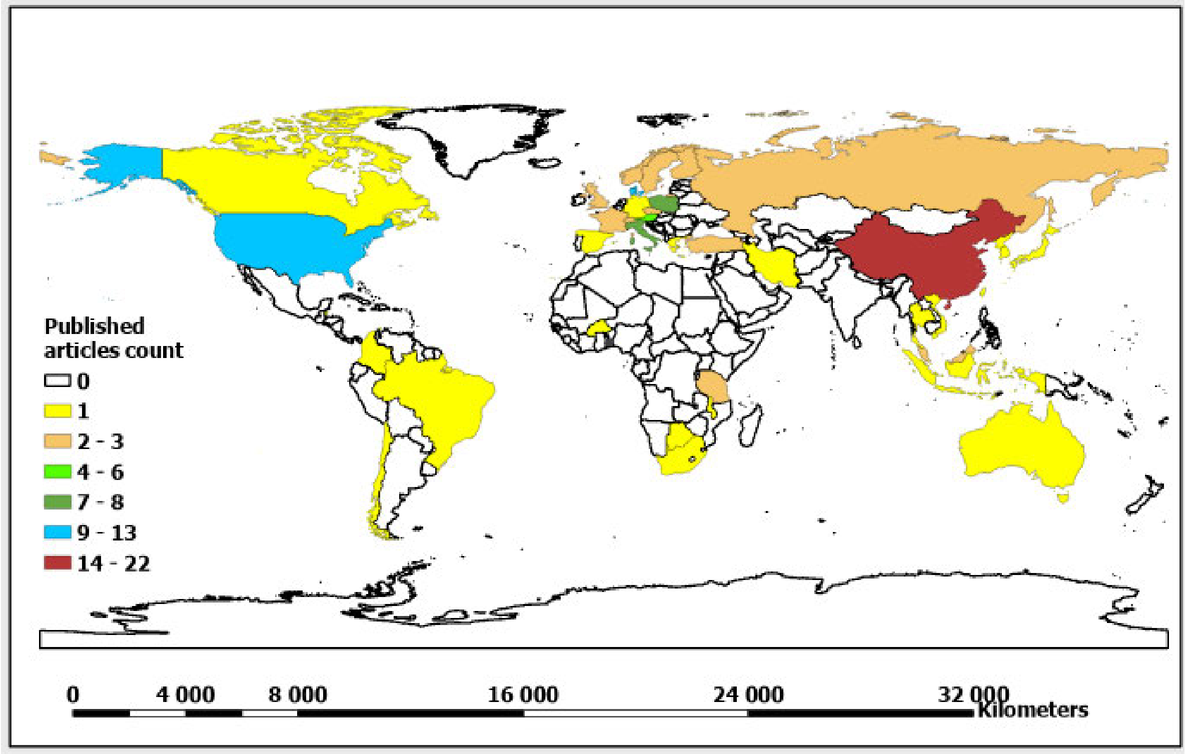



Figure 2.5. Spatial distribution of UAV-based remotely sensed data studies in the context of water levels mapping.

### 3.3. Types of UAV platforms utilised in the reviewed literature

Approximately thirty-eight drone models were used in detecting and mapping water levels in small water bodies in reviewed studies. Figure 2.6 excludes nineteen drone models reported in only one study, highlighting those used in multiple publications as the preferred drone systems in mapping water levels in small water bodies. The findings of this review illustrated that 86.7% of the studies focusing on mapping water levels in rivers and dams using drones were conducted using rotary-wing platform systems, and 13.3% were based on fixed-wing platforms (Figure 2.6). Specifically, the DJI Phantom 35.7% and DJI Matrice 15.3%, were the dominant DJI platforms noted in the reviewed studies (Figure 2.6). This could be attributed to the fact that the DJI platforms seem to be compatible platforms that can be integrated with many types of sensors, as illustrated in Table 2.2, when compared to other platforms (Schumann et al., 2019). The dominance of the multi-copter platforms in water resources mapping could be attributed to their lower cost than fixed-wing platforms (Gao et al., 2019; Zhou et al., 2025b). The superiority of the multi-rotor platforms was better established in the context of two-dimensional surface water mapping, as is the case with mapping open surface water. Particularly, the multi-copter platforms have a vertical take-off and landing (VTOL) capability, which makes it easy to utilise them in various study sites, when compared to a fixed-wing platform, which requires a runway to take off. This makes them easy to utilize various study sites, when compared to a fixed-wing platform. However, the weight of multi-copter drone batteries and their capacity limit their flight duration significantly (Zaludin & Harituddin, 2019) (see Table 2.3).

Meanwhile, fixed-wing drone platforms, such as 7A tailless fixed-wing 2.04%, were reported in mapping linear features (i.e., rivers). They were also associated with longer flight duration compared to multi-rotor systems. Their primary limitation lies in the requirement for runways during take-off and landing, which restricts operational flexibility in certain environments. Overall, DJI models were the most widely used platforms for mapping water levels in dams and rivers across the reviewed studies (Figure 2.6).

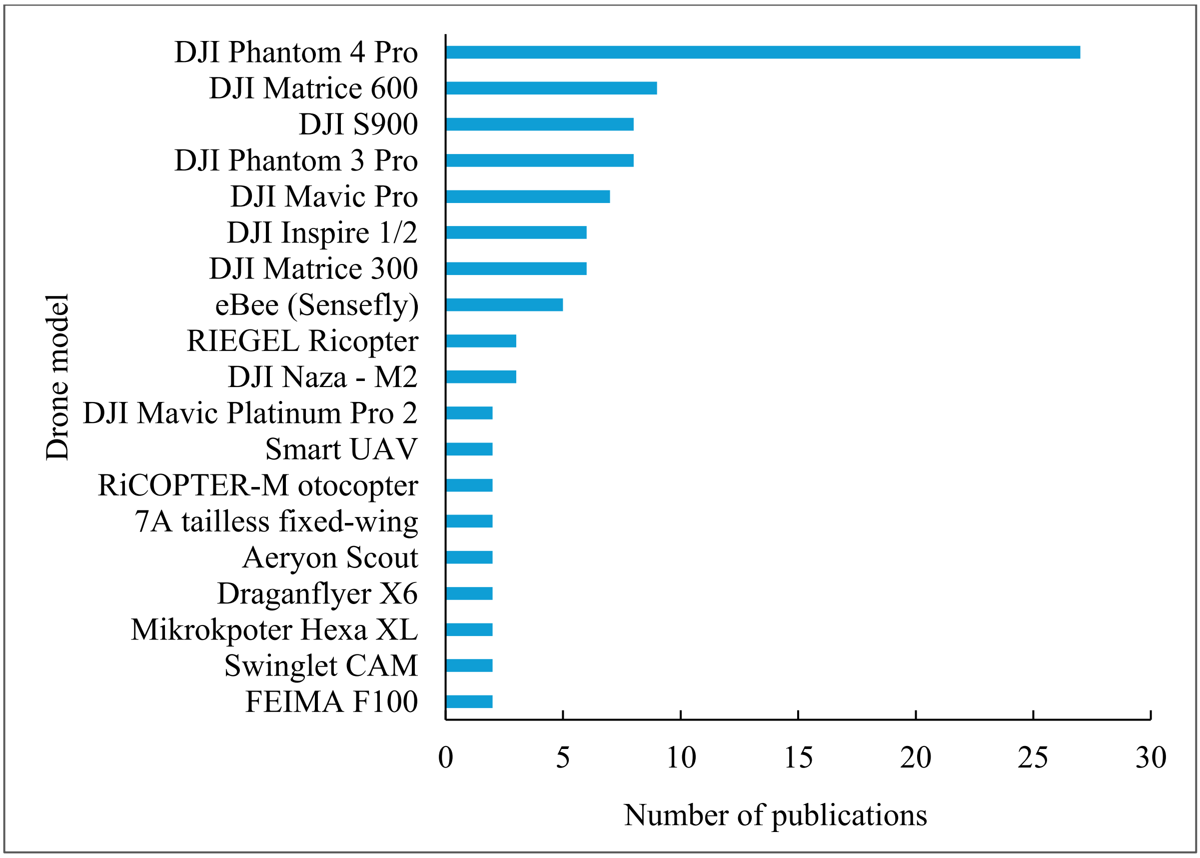



Figure 2.6. Publication frequency across the most widely used UAV platform models.

### 3.4. UAV-borne sensor technologies for water level detection and mapping in rivers and dams

In remote sensing, the characteristics of sensors play a crucial role in determining water quantity parameters. Various sensors and techniques, including LiDAR, laser distance meters, multispectral, thermal and radar data have been used for water level measurement in the reviewed literature (Figure 2.7). Multispectral and thermal imaging onboard UAVs are particularly useful in detecting water boundaries, while LiDAR demonstrated high accuracy in generating elevation profiles for water levels analysis (Bandini et al., 2020; Chen et al., 2020).

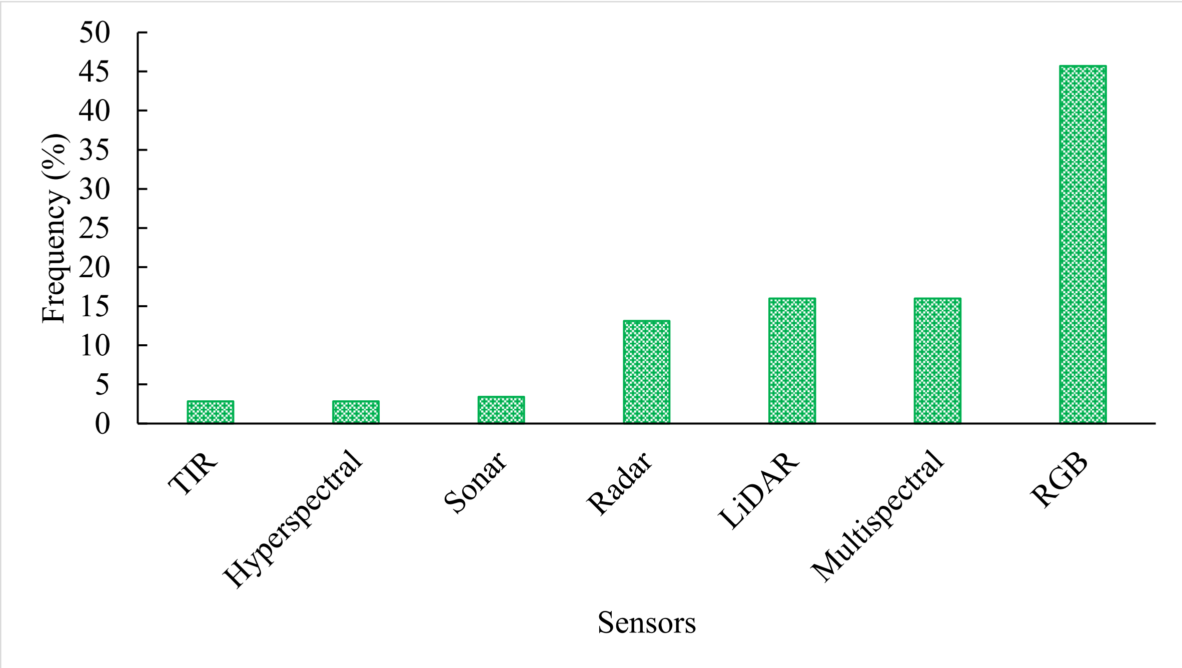



Figure 2.7. Frequency of studies that utilised a specific sensor system within the reviewed studies. Studies with multiple sensors were counted several times. TIR = thermal infrared; LiDAR = light detection and ranging; RGB = red, green, blue.

The RGB sensors are the most utilized (45.71%), including Canon PowerShot G5/Canon EOS, Zenmuse FC300X, GoPro Hero3 and Canon PowerShot ELPH 110 HS (Table 2.2, Figure 2.7). For example, Lejot et al. (2007) tested Canon PowerShot G5 and Canon EOS 500 on different channel reaches located in the south-east part of France along the Ain and upper Drome rivers. The cameras provide flexible, very high-resolution (VHR) data for channel water levels, depth (bathymetry) and gravel bar geometry, obtaining an accuracy $R^2$ of (0.59 and 0.90m) for both rivers, respectively.

Meanwhile, the multispectral sensors were utilised in 16% of the retrieved studies (Figure 2.7). Multispectral cameras acquire data not only in the visible section but also cover the near-infrared and the thermal infrared sections of the electromagnetic spectrum at high spatial resolutions. Their spectral resolution makes them sought-after for monitoring water surface extent (Cillero Castro et al., 2020; Pai et al., 2017), particularly in rivers and dams (Barros et al., 2025). For example, the 6X Sentara and Red Edge MicaSense sensors facilitate water surface extent delineation through spectral band analysis, enabling accurate mapping of small water bodies for hydrological monitoring (Table 2.2). Barros et al. (2025) employed RGB and NIR imagery to map changes in the surface extent of Ibirapuera Park lakes in the city of São Paulo, Brazil. The complex hydrological network within the densely urbanised environment was accurately mapped, yielding a root mean square error (RMSE) of 0.48, which demonstrates the robustness of the sensors. Similarly, Tymków et al. (2019), delineated water body extents using UAV-derived data from six sites in Poland, encompassing four river sections, an abandoned riverbed, and part of a lake shore. These areas are characterized by varying vegetation cover adjacent to the water body, dense vegetation behind the embankments, and medium water levels (Tymków et al., 2019). Despite the complexity of the environment, an average kappa coefficient exceeding 0.9 was achieved for water body identification. This underscores the reliability and robustness of the sensors, while demonstrating consistency with results reported in similar studies. Such analyses facilitate the detection of spatial and temporal variations in water body extent and enable high-resolution surface feature identification at scales 0.05–0.20 m (Flener et al., 2013). However, this approach is limited to surface observations and cannot directly measure water depth (Flener et al., 2013; Lejot et al., 2007).

In addition to photogrammetric approaches, UAV-mounted LiDAR sensors were frequently reported in the reviewed literature (16%), including RIEGL BDF-1 (Backes et al., 2020; Legleiter & Harrison, 2018; Legleiter & Harrison, 2019); HDL-32E Velodyne Lidar (Bandini et al., 2020; Pricope et al., 2020; Tymków et al., 2019), Phoenix Scout SL1 (Chen et al., 2021; Chen et al., 2020), LiDAR DJI Zenmuse L1 (García-López et al., 2023), (Table 2.2, Figure 2.7). LiDAR has emerged as a preferred technology since 2020 (Figure 2.2), valued for its operational simplicity and capacity to generate intuitive, high-resolution datasets. The system functions by emitting laser pulses and analysing their reflected signals to calculate precise distance measurements (Bandini et al., 2020). This capability enables the generation of high-resolution, georeferenced elevation models, which prove particularly valuable for efficient and cost-effective mapping of rivers and reservoirs (Tymków et al., 2019; Zhou et al., 2025b).

Topo-bathymetric LiDAR and near-infrared LiDAR sensors have proven particularly effective for detecting river water levels (Mandlburger et al., 2020). Reported accuracies include vertical precision of ±0.10-0.13m and spatial resolution of up to 0.02m at a 20m range, demonstrating the capability of these sensors for high spatial and temporal resolution small water bodies mapping.

Radar technologies were also reported in 13.14% of the studies as feasible for mapping water levels in small water bodies (Figure 2.7). Sensors utilised include the Geolux LX-80 AB (Jiang et al., 2020; Jiang et al., 2022; Kinzel et al., 2024; Zhou et al., 2025b), the IWR1443 ground-penetrating radar (Bandini et al., 2020; Jiang et al., 2022; Zhou et al., 2025b), radar altimetry systems (Bandini et al., 2023; Bandini et al., 2020; Jiang et al., 2022; Zhou et al., 2025b) (Table 2.2)**Error! Reference source not found.**. Zhou et al. (2025b) assessed water surface elevation (water levels) along a 10km stretch of the Ronne River in Sweden using two radar sensors. The same study evaluated Geolux LX-80, which has a measurement rate of 10Hz and an accuracy of less than 3cm (1.5cm), and the IWR1443 (legacy), which operates at 5Hz with RMSE accuracy of 3cm. Meanwhile, water penetrating radar (WPR) devices (Gekko 80, Zond Aero LF) and sonar sensors (ECT400S, ECT400, Deeper CHIRP Plus) achieved <10 cm accuracy, validated using a DJI Zenmuse L1 LiDAR (240,000 pts/s, cm-level accuracy in the same study.

Sonar-based approaches were also effective for bathymetric mapping. UAV-controlled tethered floating sonar systems (3.43%), demonstrated consistent accuracy across diverse environments. Bandini, et al. (2018b) applied this technique in a lake and two rivers in Denmark, reporting accuracies of 2.1–3.8% of actual depth for measurements up to 35 m. Depths ranging from 0.5 to 80 m were recorded, with performance unaffected by turbidity, bedforms, or substrate type (Table 2.2). This method is particularly suitable for surveying unnavigable, inaccessible, or deep-water environments where optical and LiDAR techniques are constrained.

Hyperspectral sensors represented 2.86% of the reviewed literature and included the Rikola 2D Nano Hyperspec (Gentile et al., 2016) and HySpex Mjolnir V-1240 (Legleiter & Harrison, 2019a) (Figure 2.7). For example, Gentile et al. (2016) mapped map water levels along the Ain River in France, demonstrating that UAV hyperspectral imagery (RGB Olympus and Rikola 2D) can achieve cm-level resolution. Modelled water depths had average errors <0.13 m for depths ranging from 0.09 to 1.01 m. The Rikola 2D sensor enables the acquisition of 16 spectral bands in full-frame mode or up to 24 bands in half-frame mode (1024 × 648 pixels) per hypercube. However, it was limited to the 500–900 nm spectral range and demonstrated reduced applicability for detecting and mapping water levels across varied hydrological conditions.

Thermal infrared sensors (TIR) were the least utilised within the reviewed literature. For example, the Optris PI Lightweight 450 was used by Tymków et al. (2019) at six test sites in Poland, covering rivers with differing topography, vegetation, and flow. While TIR data alone were insufficient for accurate water-level mapping, integration with RGB imagery (RGB+TIR) and laser scanners enhanced water surface detection. Overall, studies consistently showed that reliable estimates of water surface extent and depth often required combinations of sensor modalities, particularly RGB or multispectral cameras paired with LiDAR (Gentile et al., 2016; Tymków et al., 2019; Zhou et al., 2025b).

Across sensor categories, radar and LiDAR systems exhibited substantially lower mean RMSE values than RGB-based approaches (Table 2.2); however, between-category differences were not considerable at the 95% assertion stage ($p > 0.05$), primarily due to high inter-study variability and limited number of studies. Radar-based methods demonstrated a significant improvement over RGB sensors ($p = 0.068$), suggesting superior accuracy for water level estimation, while LiDAR systems showed consistently low RMSE values with broader confidence intervals reflecting sensor and methodological preferred sensor in mapping water levels in rivers and dams.

Table 2.2: Summary of UAV-sensor types used for water level estimation in reviewed literature.

| Sensor category | Sensor type | Examples | Spectral features | Application | Average RMSE (m) | Key References |
|---|---|---|---|---|---|---|
| RGB | Optical (Visible spectrum) | Canon PowerShot G5 | Broad visible bands (Blue ≈450 nm, Green ≈550 nm, Red ≈650 nm); colour and texture features | Water surface delineation, shoreline extraction, SfM-derived DEM generation | 0.37 | Gentile et al. (2016)<br>Lejot et al. (2007) |
| | | Zenmuse FC300X | RGB reflectance; intensity and texture information | Water extent mapping, small-reservoir monitoring | 0.37 | Alvarez et al. (2018)<br>Woodget et al. (2015) |
| | | RGB OLYMPUS EP-2 | Visible-spectrum reflectance; image texture and edge features | Shoreline detection, photogrammetric surface modelling | 0.25 | Flener et al. (2013)<br>Gentile et al. (2016) |
| | | RGB CMOS | Broad-band RGB reflectance; high spatial detail | High-resolution water boundary extraction, texture analysis | 0.81 | Coppo Frias et al. (2025)<br>Duan et al. (2023)<br>Witek et al. (2025) |
| | | DJI FC6310 | RGB reflectance; radiometric intensity values | UAV-based water surface mapping and elevation estimation | 1.09 | He et al. (2024)<br>Mancini et al. (2024) |
| | | DJI Zenmuse X5S | RGB reflectance; enhanced dynamic range and texture metrics | Precise shoreline mapping, SfM DEMs for water level estimation | 1.25 | La Salandra et al. (2025)<br>Zingaro et al. (2022) |
| | | DJI FC300 | Visible RGB bands; water-edge detection | Water body detection in small lakes and reservoirs | 1.61 | Yang, et al. (2019a)<br>Li 2025 |
| | | Sony ILCE-a6000 | RGB reflectance; spatial and textural descriptors | Photogrammetric modelling of water surfaces and surrounding terrain | 0.057 | Szostak et al. (2023)<br>Szostak et al. (2024) |
| | | OAK-1 Lite | RGB intensity and stereo texture features | Stereo-based surface reconstruction and water extent mapping | 1.33 | La Salandra et al. (2023)<br>La Salandra et al. (2025) |
| | | Sony NEX-5N | Visible-band reflectance; fine-scale spatial features | High-resolution shoreline extraction and DEM generation | 0.19 | Backes et al. (2020)<br>Woodget et al. (2019) |
| | | Canon EOS 550D/500 | RGB reflectance; photogrammetric texture | SfM-based terrain and water surface modelling | 0.13 | Langhammer et al. (2017)<br>Miřijovský and Šulc-Michalková (2014) |
| | | Sony Alpha 7R | High-resolution RGB reflectance; surface texture | Ultra-high-resolution water surface and shoreline mapping | 0.051 | García-López et al. (2022)<br>Ridolfi and Manciola (2018) |

| | | | | | | |
|---|---|---|---|---|---|---|
| Multispectral | Optical (RGB, NIR, Red-Edge) | RedEdge MicaSense | Blue, Green, Red, Red-Edge (≈717 nm), NIR (≈840 nm); water indices (NDWI) | Lake depth inversion, water index computation for water surface delineation (NDWI) | 0.15 | Gafurov et al. (2024)<br>Wang et al. (2025)<br>Legleiter and Harrison (2024) |
| | | Sony ILCE/A-5100 | RGB + modified NIR bands; reflectance ratios | Multispectral water mapping and band-ratio depth modelling | 1.30 | He et al. (2022)<br>He et al. (2023) |
| | | 6X Sentara | Multispectral bands including Red-Edge and NIR, and water contrast indices | Surface water detection and spectral index-based depth estimation | 1.56 | Bandini et al. (2020)<br>Yang, et al. (2019b) |
| | | Sony RX100 | Multispectral reflectance (modified sensors); band ratios | Shallow water mapping and spectral feature extraction | 0.48 | Massuel et al. (2022)<br>Templin et al. (2018) |
| | | Hasselblad X2D 100C | High-dynamic-range multispectral reflectance | High-fidelity multispectral surface characterization | 0.057 | Szostak et al. (2023)<br>Szostak et al. (2024) |
| Radar | Active microwave | Radar Geolux LX-80 AB (LX80) | Microwave backscatter intensity; phase and Doppler shift | Water level monitoring, surface elevation change detection | 0.03 | Jiang et al. (2022)<br>Zhou et al. (2025b) |
| | | Radar altimetry | Radar echo time delay; surface elevation measurements | Lake and reservoir water level mapping | 0.19 | Zhou et al. (2025b)<br>Coppo Frias et al. (2025) |
| | | Continental RS 30X | Radar backscatter and ranging metrics | Radar-based water surface elevation measurement | 0.273 | Bandini, et al. (2017a)<br>Bandini, et al. (2017b) |
| | | Radar (IWR1443) GPR | FMCW radar returns; subsurface radar wave reflections range and velocity information | Near-surface water level and wave motion sensing | 0.03 | Zhou et al. (2025)<br>Coppo Frias et al. (2025) |
| Sonar | Acoustic (single-beam, multiple-beam) | Deeper Smart Sonar CHIRP+ (Deeper, UAB Lithium) | Acoustic frequency response; echo intensity and travel time | Direct bathymetric depth measurement and validation data collection | 0.21 | Bandini, et al. (2018a)<br>Zhou et al. (2025b) |
| LiDAR | Active laser scanning | ASTRA Lite edge | Laser wavelength (≈905 nm); point-cloud intensity and elevation | High-resolution terrain and water surface elevation modelling | 0.72 | Kinzel and Legleiter (2019)<br>Legleiter and Harrison (2019) |
| | | RIEGL BDF-1 | Green laser (≈532 nm); bathymetric return intensity | Bathymetric mapping of clear and shallow water bodies | 0.26 | Backes et al. (2020)<br>Legleiter and Harrison (2019) |
| | | DJI Zenmuse L1 Livox Lidar | Laser pulse returns; 3D point clouds and reflectance | Integrated topographic mapping and water surface elevation extraction | 0.01 | Gao et al. (2019)<br>Zhou et al. (2025b) |
| | | RIEGL VQ-880-G | Green LiDAR wavelength; water surface and bottom returns | Bathymetry and water-edge mapping | 0.09 | Awadallah et al. (2023)<br>Mandlburger et al. (2021) |

| | | | | | | |
|---|---|---|---|---|---|---|
| | | RIEGL VQ-840-G | Green bathymetric laser; water depth penetration metrics | High-precision lake and river bathymetry | 0.09 | Awadallah et al. (2023) Mandlburger et al. (2020) |
| Thermal infrared (TIR) | Passive thermal imaging | Optris PI Lightweight 450 | Near-infrared reflectance (≈700–900 nm); water–land contrast | Water line detection, water surface detection | 0.50 | Bandini et al. (2020) Tymków et al. (2019) |
| | | FLIR BOSON | Thermal emission bands (8–14 µm); surface temperature gradients | Water surface detection | ---- | Medvedev et al. (2020) |
| Hyperspectral | Optical | Rikola 2D Nano, HySpex Mjolnir V-1240, CHAI V-640 | Strong absorption in NIR (≈700-1300nm) and SWIR (≈1300 – 2500nm) | Water depth mapping and water surface extent mapping | 0.13 | (Gentile et al., 2016) |

Where SfM = structure from motion; NDWI = normalized difference water index; FMCW= frequency-modulated continuous waves; NIR = near-infrared; LiDAR = light detection and ranging; GPR = ground penetrating radar; DEM = digital elevation model, SWIR = short wave infra-red; RMSE = root mean square error; $R^2$ = average coefficient of determination; m = meters; ≈ = approximately.

### 2.3.5. Data integration strategies and their impact on water level estimation

Multi-sensor integration has become a central approach in UAV-based water level estimation, enhancing both vertical accuracy and spatial resolution. UAV platforms equipped with RGB, multispectral, LiDAR, radar altimetry, sonar, and high-precision GNSS sensors enable integrated mapping of water extent, water surface elevation (WSE), and surrounding topography (Bandini et al., 2020; Hu et al., 2025). The fusion of UAV-derived DEMs with spectral imagery supports accurate shoreline extraction and WSE retrieval. Radar altimetry consistently demonstrated centimetre-level accuracy (RMSE = 0.03 m), outperforming LiDAR and photogrammetry, which commonly reported decimetre-level errors (Bandini et al., 2020; Hu et al., 2025; Zhou et al., 2025b).

The integration of sonar and water-penetrating radar further strengthened water level assessments, with contactless radar approaches achieving sub-decimetre vertical precision under vegetated conditions (Hu et al., 2025). For instance, Coppo Frias et al. (2025), implemented a multi-sensor UAS framework across 50 cross-sections of the Rya River, integrating sonar (Deeper Smart Sensor Chirp+), LiDAR (Velodyne VLP-16), radar altimetry (IWR1443), and photogrammetric RGB data. LiDAR-derived elevations yielded an average RMSE of 0.461 m, while sonar-based bathymetry achieved higher accuracy (RMSE = 0.162 m). Radar altimetry produced WSE estimates ranging from 0.12 to 1.25 m across surveyed transects.

Cross-platform data fusion between UAV and satellite sensors has expanded monitoring from local to catchment scales, improving seasonal and interannual water level analyses. For example, Li et al. (2025) integrated Landsat 5, Landsat 8, Sentinel-2, and UAV-derived RGB imagery, with total station measurements for calibration and validation, to assess seasonal water level dynamics in the middle reach of the Yellow River, China. Spectral–spatial enhancement techniques, including index-based water extraction combined with machine learning models, further improved delineation accuracy (Lee et al., 2022). Combining UAV-borne sensor data with artificial intelligence–driven oriented synthetic aperture radar (SAR) methods, especially those using edge-aware deformable convolution and point set representation-enhances water surface delineation and improves water level retrieval accuracy in small water bodies (Guan et al., 2025; Li et al., 2024).

Despite these advantages, multi-sensor frameworks introduce increased calibration complexity, higher operational costs, and limited methodological standardisation. Overall, integrated UAV sensing significantly improves the precision and reliability of water level estimation, although rigorous calibration and harmonised workflows remain essential for reducing bias and ensuring reproducibility.

### 3.3.6. Bias assessment, sensor calibration and validation methods

Bias assessment of sensor calibration and validation methods in the reviewed literature was conducted based on the application of ground control points (GCPs), radiometric and geometric calibration procedures, and cross-sensor validation approaches (Kim et al., 2019; Ngo et al., 2025). The evaluation also considered the use of independent ground-truth measurements for calibration and validation, including Real-Time Kinematic Global Positioning System (RTK GPS), Real-Time Kinematic Global Navigation Satellite System (RTK GNSS), Acoustic Doppler Current Profiler (ADCP) attached on a boat, water level meters, hygrometric station measurements, echo sounders, levelling rods, calibrated dip sticks, and GNSS and inertia measurement unit to align measurements with real-world coordinates (Table 2.3). Additional assessment criteria included the incorporation of cross-sectional surveys, as they enhance the reliability, reproducibility, and interpretability of remotely sensed water level estimates. More so, appropriate data splitting for calibration and validation, and the reporting of performance metrics such as the coefficient of determination ($R^2$) and root mean square error (RMSE) was also considered (Table 2.4). A chi-square goodness-of-fit test indicated that the proportion of low-risk studies (95%) was significantly higher than that of moderate-risk studies (5%) ($\chi^2$, $p < 0.001$). This suggests a statistically significant predominance of low-bias studies within the reviewed literature. The moderate-risk classifications were primarily associated with missing uncertainty metrics and inadequate reporting of calibration procedures.

Table 2.5. Bias assessment for observational studies, sensor calibration and validation methods.

| Study/sensor | Sensor calibration | Validation method | Sampling/site selection | Reporting transparency | Overall bias | Justification | Reference |
|---|---|---|---|---|---|---|---|
| RGB | 🟢 | 🟢 | 🟢 | 🟢 | Low | Used 7 to 77 (Av = 42) well-distributed GCPs; camera calibration described; independent RTK water level measurements (170 to 900) (Av = 535); data calibration and validation ratio specified (70:30); RMSE and R² reported; spatial validation; cross sections measurement (10-37) (Av = 24), cross sensor validation specified, software's stated, flight altitude and overlap specified. | He et al. (2022)<br>Mancini et al. (2024) |
| Multispectral | 🟢 | 🟢 | 🟢 | 🟢 | Low | Radiometric correction mentioned with detailed clear procedure; 6 to 20 GCPs used (Av = 15); independent RTK GPS and water level recorder points for validation done (171 to 10320) (Av = 2969); RMSE, R² reported, data calibration and validation ratio specified (70:30), number of cross sections specified (2 to 8) (Average = 2); cross sensor validation or sensor fusion is detailed for accuracy assessment; models clearly specified and described and replicability is detailed. | Lee et al. (2022)<br>Liu et al. (2025) |
| Radar | 🟢 | 🟢 | 🟢 | 🟢 | Low | Sampling distance stated, RTK GNSS ground truthing measured (300 to 1372) (Av = 836), ADCP, eco sounders validation measurements, cross sensor validation for accuracy assessment, different cross sections mapped and measured (7 to 13) (Av = 10), transmission loss, propagation loss, reflection loss and spread loss is detailed, environmental, water turbidity and surface status well described, MAE, RMSE reported. | Bandini et al. (2023)<br>Gu et al. (2023) |
| Sonar | 🟢 | 🟢 | 🟢 | 🟢 | Low | Sensors used are clearly specified, water levels validated with RTK GNSS, radar, water level dip meter and radar altimetry measurements; GNSS master station for differential correction stated; different cross sections mapped to check robustness of the sensors and procedure (19-50) (Av = 25); tilting, measuring angle, geometric configuration, bottom detection thresholding and overlaps well detailed; R², MAE, RMSE reported. | Bandini, et al. (2017b)<br>Coppo Frias et al. (2025) |
| LiDAR | 🟢 | 🟢 | 🟢 | 🟢 | Low | GCPs are used (8 to 12) (Av = 9); sensors and software's used are clearly stated. GNSS master station used for differential corrections. RTK GNSS, ADCP and eco sounder measurements used for validation (19 to 300) points (Av = 159); other sensors used as validation; WSE, R² and RMSE reported, | Hu et al. (2025)<br>Zhou et al. (2025b) |
| Hyperspectral | 🟢 | 🟢 | 🟢 | 🟢 | Low | Radiometric calibration procedure followed and well detailed. Methodology, data processing and models well described. Data for training and testing stated using 70:30 ratio (350 to 19025) (Av = 4843); cross calibration and validation between ADCP and eco sounder measurements to ensure consistency. Cross sensor validation clearly stated. Different cross sections used to test the feasibility of sensor and models calibration (4 to 12) (Av = 6). R² and RMSE metrics reported. | Gentile et al. (2016)<br>Legleiter and Harrison (2019) |
| Thermal infrared | 🟢 | 🟢 | 🟡 | 🟡 | Moderate | Sensors and specifications stated. GCPs used for calibration (7 to 12) (Av = 10). RTK GNSS measurements used for calibration and validation. Cross sensor validation applied, environment and challenges clearly described. Different metrics reported including R², RMSE, OA, PA and K. | Kinzel and Legleiter (2019)<br>Tymków et al. (2019) |

Rating key: 🟢 Low bias 🟡 Moderate 🔴 High bias

Where: Av = average, ADCP = acoustic doppler current profiler, GCPs = ground control points, WSE = water surface elevation, RMSE = root mean square error, MAE = mean absolute error, OA = overall accuracy, PA = producer accuracy, K = Kappa coefficients, RTK GNSS = real time kinematic global navigation satellite system, $R^2$ = coefficient of determination, LiDAR = light detection and ranging

### 2.3.7. Spectral indices and band algorithms

Water indices were also applied to UAV-borne data for detecting and mapping water surface extent. Approximately 9.5% of studies confirmed the efficiency of index-based approaches for estimating water surface extent. These methods are widely adopted due to their simplicity and cost-effectiveness compared with more complex classification techniques (Barros et al., 2025; Shangguan, 2023). The Otsu thresholding was frequently combined with index-based approaches to delineate surface water and detect changes over time (Kaya et al., 2023; Kwon et al., 2023; Liu et al., 2025). Four used indices and band combinations included the Normalised Difference Vegetation Index (NDVI), the Normalised Difference Water Index (NDWI), the Modified Normalised Difference Water Index (MNDWI) and the Automated Water Extraction Index (AWEI) were used in reviewed studies (Table 2.2). MNDWI and AWEI achieved high accuracies, with kappa coefficients of 0.96 and 0.95, and an overall accuracy of 0.98. Indices were derived from UAV-mounted multispectral and RGB sensors, using near-infrared (NIR), red, and green bands (Cillero Castro et al., 2020; Jiang et al., 2022; Kaya et al., 2023; Pai et al., 2017).

### 2.3.8. Machine learning and predictive models' performance in detecting and mapping water levels

The results of this review indicate that forty-four machine learning and predictive models have been employed for detecting and mapping water levels in small water bodies. Figure 2.8a and Figure 2.8b) present the average coefficient of determination ($R^2$) and RMSE values, respectively, for machine learning and predictive models applied in more than three studies. Thirty-six of the 44 machine learning and predictive models were excluded from Figure 2.8a and Figure 2.8b because they were applied in less than three studies. Machine learning and predictive models exhibit varying performance in the estimation of water levels. The comparative evaluation of machine learning models revealed that nonlinear and deep learning approaches achieved consistently high predictive performance. Convolutional neural networks (CNNs) exhibited an average $R^2$ of approximately 0.94–0.96, while random forest (RF) and support vector machine (SVM) showed average $R^2$ values around 0.93–0.95 and 0.92–0.95, respectively (Figure 2.8a and Table 2.4). Deep neural networks (DNNs) demonstrated similarly strong performance with an average $R^2$ ranging between 0.91–0.93 (Figure 2.8a and Table 2.4). These models also displayed relatively narrow interquartile ranges, indicating stable performance across reviewed studies.

In contrast, multiple linear regression (MLR) showed a substantially lower median $R^2$ of approximately 0.58–0.62, with a widespread ranging roughly from 0.45 to 0.78, reflecting considerable variability and reduced predictive robustness. Other models such as K-nearest neighbours (KNN) attained an average $R^2$ ranging from 0.84 to 0.86 and optical band ratio analysis (OBRA) have an average range between 0.80 to 0.83, Figure 2.8, demonstrated moderate predictive capability.

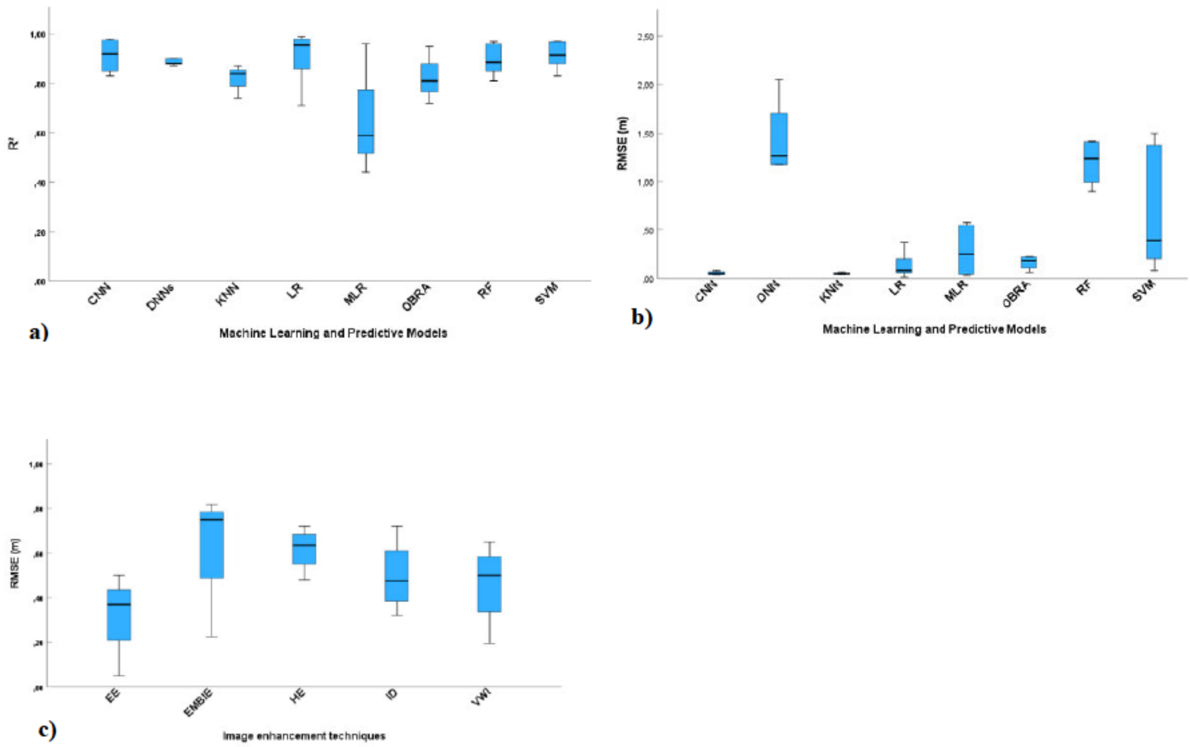



Figure 2.8 Machine learning and predictive models' performance in reviewed studies. R2 and RMSE for machine learning and predictive models (a) and (b), and RMSE for image enhancement techniques utilised in reviewed studies (c). (a) CNN = convolutional neural networks; DNNs = deep neural networks; KNN = k (number) nearest neighbours; LR = linear regression; MLR = multiple linear regression; OBRA = optimal band ratio analysis; RF = random forest; SVM = support vector machine. (b) EE = edge enhancement; EMBIE = empirical model-based image enhancement; HE = histogram equalisation; ID = image differencing; VWI = vegetation and water index.

Overall, these results indicate that nonlinear and deep learning approaches explain approximately 90–96% of the variance in UAV-derived water level data, whereas traditional linear models such as MLR account for only about 60% of the variance, underscoring the superior capability of advanced machine learning techniques in modelling the complex nonlinear relationships inherent in UAV-based hydrological applications.

The RMSE comparison reveals that CNN and KNN achieved the lowest median errors (<0.1 m), indicating superior accuracy in UAV-based water level estimation (Figure 2.8b). LR and OBRA demonstrated moderate performance, attaining an average RMSE of 0.15–0.22 m, while MLR showed slightly higher error of approximately 0.30 m. In contrast, RF and DNN exhibited substantially larger RMSE values (>1.0 m), and SVM showed considerable variability. These results suggest that certain nonlinear approaches, particularly CNN, provide more precise water level predictions, whereas model performance remains highly context-dependent in UAV hydrological applications.

Table 2.6. Accuracy measure for water level machine learning and modelling methods.

| Algorithm | Abbreviation | Metric ($R^2$) | Metric (RMSE) | Key References |
|---|---|---|---|---|
| Convolutional Neural Network | CNN | 0.83 – 0.98<br>average 0.93 | 0.041 – 0.073<br>average 0.057 | Szostak et al. (2023)<br>Szostak et al. (2024) |
| Deep Neural Networks | DNN/s | 0.87 – 0.90<br>average 0.88 | 0.19 – 2.05<br>average 1.19 | He et al. (2023)<br>Liu et al. (2025) |
| K-Nearest Neighbours | KNN | 0.74 – 87<br>average 0.81 | 0.038 – 0.065<br>average 0.039 | La Salandra et al. (2023)<br>Mandlburger et al. (2020) |
| Linear Regression | LR | 0.71 – 0.99<br>average 0.92 | 0.01 – 3.13<br>average 0.35 | Gutsa et al. (2024)<br>Wang et al. (2025) |
| Multiple linear Regression | MLR | 0.44 - 0.86<br>average 0.71 | 0.03 – 2.42<br>average 0.64 | Kujawa et al. (2025)<br>Wang et al. (2022) |
| Optimal Band Ratio Analysis | OBRA | 0.72 – 0.95<br>average 0.82 | 0.06 – 0.22<br>average 0.16 | Legleiter and Harrison (2018)<br>Legleiter and Harrison (2024) |
| Random Forest | RF | 0.81 – 0.96<br>average 0.90 | 0.90 – 1.41<br>average 1.22 | Gafurov et al. (2024)<br>He et al. (2024) |
| Support Vector | SVM | 0.83 – 0.89<br>average 0.86 | 0.39 – 1.37<br>average 0.88 | He et al. (2024)<br>Liu et al. (2025) |
| Edge Enhancement | EE | | 0.05 – 0.5<br>average 0.31 | Agrafiotis et al. (2019)<br>Ridolfi and Manciola (2018) |
| Empirical Model-Based Image Enhancement | EMBIE | | 0.225 - 0.82<br>average 0.60 | Bandini, et al. (2017a)<br>Lejot et al. (2007) |
| Histogram Equalisation | HE | | 0.48 – 0.72<br>average 0.62 | Hout et al. (2020)<br>Legleiter and Harrison (2019) |
| Vegetation and Water Index | VWI | | 0.195 – 0.65<br>average 0.48 | Barros et al. (2025)<br>Kaya et al. (2023) |
| Image Differencing | ID | | 0.32 – 0.72<br>average 0.50 | Barros et al. (2025)<br>Shangguan (2023) |

### 2.3.9. Image enhancement techniques performance in the reviewed literature

Image enhancement techniques also play a crucial role in improving the visual quality and analytical accuracy of UAV-derived imagery. Figure 2.8c presents the average RMSE values for image enhancement techniques applied in more than three studies. Three of the 8 image enhancement techniques were excluded from Figure 2.8c since they were applied in less than three studies. Regarding the performance of image enhancement techniques, edge enhancement (EE) achieved an average RMSE value of 0.35 m, demonstrating superior accuracy in UAV-based water level estimation (Figure 2.8c and Table 2.4). Meanwhile, vegetation and water index (VWI) attained an average RMSE value of 0.46 m and image differencing (ID) obtained average value of (0.50 m) showed moderate performance, while histogram equalisation (HE) has an average value of 0.62 m, which is relatively stable but higher error values. Empirical model-based image enhancement (EMBIE) exhibited both high average RMSE (~0.60 m) and substantial variability, suggesting inconsistent performance across study contexts. These findings highlight the influence of image preprocessing strategies on shoreline delineation accuracy and subsequent water level prediction reliability.

## 2.4. Discussion

### 2.4.1. Progress in remote sensing of water levels in small reservoirs and dams

#### 2.4.1.1. Geographical distribution and publication trends

This study reveals a notable increase in UAV use for water-level monitoring from 2015 onwards, likely driven by the easing of UAV regulations in the United States from 2012 and rapid advances in drone and sensor technologies (Sibanda et al., 2021). In addition, UAV-remote sensing complements ground-based observations through inversion modelling and data integration techniques (Barros et al., 2025; Lee et al., 2022; Szostak et al., 2023). Globally, UAV applications in earth observation increased from 2017 up to 2025 (Figure 2.3). Among the studies reviewed, one hundred and ten focused specifically on rivers and dams, highlighting growing research interest in flood prediction and water resource management.

The findings revealed that most studies were conducted in China, Europe and United States of America (Figure 2.5). This reflects the early adoption of UAV technology in these regions, dating back to the twentieth century (Mishra et al., 2023). Furthermore, the world's leading UAV manufacturer, DJI, headquartered in Shenzhen, China, was the most frequently used platform in the reviewed studies. The region's high concentration of research studies is likely attributable to its proximity and ready access to UAV technology. Additionally, Europe and United States of America's robust technology sector have supported the widespread adoption of UAVs in water level monitoring, resulting in a higher number of studies in the region. Overall, these countries are highly developed and have adequate resources to support water level monitoring programs.

### 2.4.1.2. UAV water level sensors

In terms of platforms and sensors, multi-copters were predominantly used in mapping water levels in reviewed studies. According to Lee et al. (2022), multi-copters are ideal for water levels mapping due to their flexibility in any environment, unlike fixed-wing, which requires a runway. The review showed that RGB sensors, including Canon PowerShot G5 and OLYMPUS EP-2, were adopted by most studies and utilised together with another sensor. RGB sensors are cheaper, and their spectral resolution is useful in modelling water levels (Gentile et al., 2016; Özcan & Özcan, 2021). This is in line with the findings of Jiang et al. (2022), Sibanda et al. (2021), Templin et al. (2018), who echo that, as the spectral resolution of drone sensors increases, the associated costs also increase linearly. However, the RGB sections of the electromagnetic spectrum alone do not offer adequate data for accurately and effectively mapping water levels, despite their relatively limited costs and very high spatial resolutions in relation to additional robust sensors (He et al., 2023; Lejot et al., 2007; Sibanda et al., 2021).

Regarding multispectral sensors, MicaSense was widely used in mapping water levels in small water bodies because it can capture images in five distinct bands: blue, green, red, near-infrared and Red Edge (Gafurov et al., 2024; Lee et al., 2022; Wang et al., 2025). These bands are crucial in estimating water surface extent using water-based index such as NDWI**Error! Reference source not found.**. Despite these strengths, their spectral sensitivity is constrained to visible and near-infrared bands and lacks short-wave infrared (SWIR) which is well suited for detecting and mapping water surfaces. This fixed hardware limitation constrained the water indices which can be computed.

LiDAR sensors were widely used in reviewed studies due to their capability in determining water surface elevation, 3D construction and depth in small water bodies (Backes et al., 2020; Schwarz et al., 2019). However, LiDAR sensors are expensive and classification of data set needs manual correction, to separate water, ground and vegetation (Zhou et al., 2025b).

In addition, radar sensors occupied the fourth position in terms of utilised sensors in mapping water levels in small water bodies (Figure 2.7). This is attributed to the fact that radar sensors directly determine water levels of the target area. Unlike LiDAR, radar signals penetrate turbid water (Bandini, 2017; Zhou et al., 2025b). The radar provided the best results and ensured the lowest processing time (Table 2.2). Hyperspectral and TIR sensors were the least utilised in the reviewed literature due to limited capabilities in mapping water levels as standalone sensors

(Gentile et al., 2016; Kinzel & Legleiter, 2019; Tymków et al., 2019). However, literature showed that integrating them with other sensors yielded the best results in water level mapping.

Multi-sensor integration significantly enhances UAV-based water level estimation by improving vertical accuracy, spatial resolution, and shoreline delineation through the fusion of DEMs and high-resolution spectral imagery. For instance, integration of radar altimetry, LiDAR and photogrammetry, produced accurate and reliable water levels under vegetated and complex surface conditions (Hu et al., 2025; Zhou et al., 2025b). The fusion of bathymetric sensors with UAV-derived topography strengthens hydro-morphological assessments, while cross-platform fusion with satellites including Landsat 8 and Sentinel-2 extends monitoring from local to catchment scales.

#### 2.4.1.3. Sensor's calibration and validation methods

The review revealed notable variability in the rigor of sensor calibration and validation procedures across UAV-based water level studies. Studies that implemented well-distributed GCPs for calibration and ortho-rectification, applied appropriate radiometric and geometric corrections, and used independent high-precision ground-truth data (e.g., RTK GPS/GNSS, ADCP, water level meters, echo sounders, levelling instruments) demonstrated lower RMSE and more reliable $R^2$ values, indicating reduced measurement bias. Conversely, inadequate documentation of calibration steps, absence of independent validation datasets, or failure to separate calibration and validation data increased the risk of positional error, overfitting, and performance inflation as shown in 5% of reviewed studies.

#### 2.4.1.4. Application of water level estimation algorithms

This review highlights the strengths and limitations of various algorithms used for assessing water levels in small water bodies from UAV-derived data. Although linear regression is the most utilised algorithm as reported in literature, it has inherent limitations in accuracy assessment (Erena et al., 2019). Water level changes are influenced by complex, non-linear factors (e.g., rainfall patterns, evaporation rates, seasonality) that linear regression cannot fully capture (Schumann et al., 2019).

In reviewed studies, convolutional neural networks (CNN/s) were the most adopted method because of its capabilities in handling non-linear multi-dimensional data. For instance, Shen (2022), Szostak et al. (2023), Szostak et al. (2024), found an average (R2 of 0.96 and RMSE of <0.1 m) with sample size of 400, 64 to 74 and 64 to 74, in three data sets between predicted and ground truth value testing data sets, showing efficiency and reliability. Nevertheless, deep learning models are based on black box models, making it difficult to interpret their outputs (Liu et al., 2025; Shangguan, 2023). The SVM was also significantly used due to its ability to excel at handling non-linear data and can effectively classify and predict water levels, even with complex, high-dimensional datasets and is less prone to overfitting. For example, Kujawa et al. (2025), Liu et al. (2025), Szostak et al. (2023) demonstrated a SVM model as the optimal choice for deep water depth inversion (average $R^2$ = 0.93, average RMSE = 0.18 m), demonstrating notable strengths in processing limited sample sizes of 88, 136 and 179), respectively. However, SVM require careful parameter tuning, selection of appropriate kernel function and regularisation parameters, which are time consuming, trial and error process, hence it is subjected to overfitting or underfitting (Agrafiotis et al., 2019; Liu et al., 2025; Zhou et al., 2023). The KNN and OBRA are other models applied in the reviewed literature as reliable models in predicting water depth, because of the simplicity of the algorithms and their effectiveness in making good predictions. However, the KNN algorithm does not create a generalised separable model, hence limited transferability to predict water depth in different small water bodies with different characteristics (Ansari et al., 2021; La Salandra et al., 2023; Legleiter & Harrison, 2018).

Meanwhile, Random Forest obtained optimal results due to its ability to capture complex, non-linear interactions resilience to noisy data, provides insights into the most influential variables through feature importance, and can handle diverse data types without extensive pre-processing, highlighting its feasibility in predicting water levels in small water bodies (Liu et al., 2025; Zhou et al., 2023). Although it demonstrates good predictive performance $R^2$ metric, its effectiveness is constrained when applied to multidimensional testing dataset with high water levels, hence higher RMSE values (La Salandra et al., 2023). The reviewed studies shows that $R^2$ alone is insufficient to evaluate model suitability; RMSE is essential for assessing practical water level prediction accuracy. Overall, reviewed studies indicate a methodological shift toward nonlinear and deep learning approaches in UAV-based hydrological monitoring, with preprocessing selection and multi-metric evaluation being critical for ensuring accurate and operationally reliable water level estimation.

#### 2.4.1.5. Image enhancement techniques

The comparative analysis of RMSE metric across image enhancement techniques reveals notable differences in accuracy and consistency for UAV-derived water level monitoring. Edge Enhancement (EE) demonstrated the lowest average values. Its lower median and narrower interquartile distribution indicate strong and relatively consistent performance. The presence of very low RMSE values suggests that EE is particularly effective in improving shoreline delineation and water boundary detection under favourable imaging conditions in rivers and dams (Giulietti et al., 2022).

Meanwhile, VWI and ID showed moderate performance, exhibiting moderate variability, suggesting reasonable stability across different study environments. Their performance indicates suitability for general water level estimation tasks. HE produced a higher average RMSE value but displayed relatively low variability, indicating stable yet consistently higher prediction errors. The results suggest that while HE may enhance overall image contrast, it may also amplify noise or non-water features, reducing boundary detection precision (Hout et al., 2020; Legleiter & Harrison, 2019). EMBIE exhibited the highest variability and relatively high average variability. The wide range indicates sensitivity to environmental conditions such as turbidity, illumination variability, and background heterogeneity (Lee et al., 2022). This inconsistency suggests that EMBIE may require additional optimisation to ensure reliable performance across diverse UAV applications in detecting and mapping water levels in small water bodies.

Overall, the findings demonstrate that image enhancement strategy significantly influences the accuracy of UAV-based water level estimation. Techniques that emphasise edge detection appear more effective for shoreline extraction, whereas histogram-based or more complex enhancement approaches may introduce variability or higher error. The results highlight the importance of selecting preprocessing methods that align with environmental conditions and sensor characteristics to improve the precision and robustness of UAV hydrological monitoring systems.

### 2.4.2. Quantitative cost-effectiveness of UAVs versus traditional water level mapping

UAV-based water level mapping offers clear cost and operational advantages over traditional methods. Conventional in situ instruments (staff gauges, pressure transducers, radar sensors) have lower initial costs (USD 500–10,000 per unit) but incur high long-term expenses from installation, calibration, maintenance, and repeated field campaigns (Masoudimoghaddam et al., 2025). Ground-based surveys are labour-intensive, costing USD 350–1,200 per day, with multi-day campaigns further increasing costs (Masoudimoghaddam et al., 2025; Purnell et al., 2021).

UAV systems require higher upfront investment (USD 1,500–30,000 for RGB platforms; USD 3,000–5,500 for multispectral; >USD 100,000 for LiDAR), but per-project costs are lower

(USD 1,300–2,500 versus USD 2,200–4,600 for traditional surveys), achieving 30–45% cost savings (Cucho-Padin et al., 2020; Wheeler et al., 2025). Low-cost UAV-mounted sensors, such as radar-sonar combinations, can further reduce system costs below EUR 1,000 while maintaining centimetre-level accuracy (Matsimbe et al., 2022). For instance, The ARS30X radar has a market price of approximately EUR 3,200, while the MB7386 sonar is priced around EUR 150 and camera-based laser distance sensor system is estimated at EUR 800 (Bandini, et al., 2017b). Break-even is typically reached after two to three repeat surveys.

UAVs provide rapid data acquisition (minutes to hours versus days), high-resolution spatial coverage, and flexible deployment, enabling water level monitoring in rivers, lakes, floodplains, and inaccessible features such as sinkholes. Unlike fixed stations, UAVs capture spatially distributed water surface elevations, water slopes, and surface–groundwater interactions and remain operational during extreme events where in situ stations often fail (Gutsa et al., 2024). Additionally, UAVs can potentially be used during extreme events when in-situ monitoring stations often fails, and satellite observations do not ensure the required spatial and temporal resolution (Gu et al., 2023). While traditional methods remain cost-efficient for long-term single-point monitoring, UAVs are more cost-effective for multi-site, repeated, and spatially explicit water level mapping, offering superior temporal and spatial flexibility.

### 2.4.3. Challenges associated with the utilisation of drone technologies in determining water levels.

Statutory regulations governing drone operations pose a major challenge to UAV-based water-level monitoring (Cracknell, 2017; Wang et al., 2024). Many countries enforce strict restrictions on flight areas, take-off mass, and maximum altitude (Lally et al., 2019). For example, the South African Civil Aviation Authority (SACAA) regulates remotely piloted and toy aircraft, prohibiting flights within 50 meters of any individual or group and limiting maximum altitude to 45.72 meters (150 feet) above ground without prior authorisation (Mokoena et al., 2022; Sibanda et al., 2021).

Technical and environmental factors further complicate UAV water-level measurements. Noise sources such as camera tilt, wind and vegetation can reduce accuracy, while the presence of vegetation can obscure the water-land boundary, creating significant errors (Kujawa et al., 2025). Mapping complex river channels and estimating water volume require robust sensors capable of penetrating water, as lakebed elevations are influenced by sedimentation, erosion, geological event, and anthropogenic activities (Abdelal et al., 2021; Ben Moshe & Lensky, 2024).

Additionally, water strongly absorbs wavelengths used by LiDAR systems, particularly near-infrared (NIR), which can degrade laser pulse reflections and reduce measurement accuracy (Pingel et al., 2021). Active sensors combined with advanced machine learning algorithms can help ameliorate these limitations. For instance, (Zhao et al., 2023) applied LSC super pixel segmentation fused with enhanced GrabCut algorithm and Sobel edge detection to perform intelligent segmentation and dam extraction from high-resolution UAV imagery. This approach successfully detected changes in reservoir dams in Guilin, demonstrating the technical feasibility of systematic, full-coverage UAV-based monitoring of multiple reservoirs.

Another challenge is the use of seventy-eight different cameras and forty-one different UAV models, several different methodologies and algorithms in reviewed studies. The review highlights that UAV-based remote sensing methods for mapping water levels in small water bodies lack standardisation.

In summary, the main challenges in UAV water-level monitoring arise from regulatory constraints, environmental interference, sensor limitations, and data-pre-processing complexities. Addressing these challenges requires a combination of flexible regulatory frameworks, robust sensor technologies, and advanced computational methods, which together can enable accurate, large-scale, and reliable water-level assessment using drones.

### 2.4.4. Research Gaps and Way Forward

Despite growing interest, several gaps remain in UAV-based water level monitoring:

- Limited Focused Research: Few studies specifically target mapping water levels in rivers and dams using UAV data. Future research should focus on leveraging UAV-derived datasets for precise quantification.
- Underutilisation of LiDAR Sensors: UAV-mounted LiDAR remains largely unexplored, despite its potential for high-resolution measurements.
- Need for Sector-Specific Studies: Most research generalises UAV applications. Therefore, targeted studies on rivers and dams are needed to optimise methodologies.
- Reservoir Monitoring: The viability of UAVs for monitoring reservoir water levels under varying hydrological conditions requires evaluation.

- Agricultural Applications: UAVs can help monitor water levels near farms to address climate variability, unpredictable rainfall, and water management.
- Accuracy and Resolution Limitations: The feasibility of obtaining highly accurate, high-resolution measurements remains poorly documented.
- Artificial Intelligence (AI), Deep Learning and Machine Learning: AI, deep learning and machine learning should be applied to correct noise, reduce positional errors (He et al., 2022), and analyse water level dynamics (Duan et al., 2023; Lee et al., 2022; Quesada-Román et al., 2020).
- Scaling and Operationalisation: While UAV studies are often site-specific, future work should address scalability. Hybrid systems integrating UAV data with satellite imagery could provide both high-resolution local monitoring and regional coverage. Developing cost-effective operational frameworks will be essential for implementation in vulnerable rural communities in developing regions.
- Flood Risk Monitoring and Rapid Assessment: Future studies should investigate automated workflows for near-real-time water level extraction and shoreline delineation to improve small-reservoir flood risk mapping. Coupling UAV-derived digital elevation models (DEMs) with hydrodynamic simulations could improve understanding of overtopping risks and downstream flood propagation.
- Integration of UAVs into Climate-resilient and Drought Early Warning Systems: Future research should explore how high-resolution UAV-derived water level data can be integrated towards climate-resilient water management and drought forecasting models, particularly in small reservoirs that are highly vulnerable to hydrological variability.
- Integrated Data Systems: Opportunities exist to coordinate UAV data collection, develop processing systems, and integrate multi-source datasets to enhance monitoring accuracy.

Addressing these gaps will strengthen UAVs as reliable tools for water-level monitoring, providing timely, accurate, and actionable information for water management, agriculture, and flood-risk mitigation.

### 2.4.5. Limitations of the study

Some articles were unavailable in full text, which constrained the comprehensiveness of the review. In addition, excluding non-English publications may have reduced the number of studies considered on water levels in small water bodies. The accuracy of remote sensing data plays a vital role in ensuring the reliability of the results, as errors or uncertainties in the data can significantly influence analysis and interpretation. This review relied primarily on RMSE and $R^2$ values to assess accuracy, which represents a limitation. Moreover, the reliability of RMSE and $R^2$ is contingent upon several methodological and data-related factors, including sample size, sensor specifications, algorithmic approaches, and the applied water indices. Reviewed studies adopted a range of accuracy assessment metrics, with reported results expressed in heterogeneous and non-uniform International System of Units (SI), limiting comparability across studies. These factors should be integrated into the final analysis to enhance the reliability, interpretability and reproducibility of the findings. Consequently, by limiting the review to peer-reviewed literature, the reported accuracy metrics are presumed to reflect robust and credible by reviewers.

### 2.5. Conclusions

The objective of this study was to conduct a systematic review on the utility of UAV-remotely sensed data for detecting and mapping water levels in small water bodies and assessing the progress, opportunities and challenges. The review shows that UAVs are feasible in detecting and mapping water levels in rivers and dams. A total of one hundred and ten studies has investigated water levels in rivers and dams using UAVs equipped with various sensors and platforms. The results show that the use of remotely sensed data in detecting and mapping water levels was well incorporated, as indicated by an increase in its use from 2015. The outcomes demonstrate that the DJI platform was the most used due to its compatibility with a wide range of sensors. Multispectral, RGB, radar and LiDAR sensors were the dominantly used due to their capability to accurately capture water surface extent and depth. However, it remains necessary to accurately evaluate specific sensors in combination with machine learning algorithms for assessing water levels in rivers and dams. Future research should focus on large-scale validation studies and automated data processing to maximise UAV utility in water resource management.

# Chapter Three

**Integrating UAV remote sensing and machine learning techniques to quantify water level fluctuations in small reservoirs.**

This chapter is based on:

Elvis Mawodzeke, Tsitsi Bangira, Mbulisi Sibanda, Onisimo Mutanga, and Tafadzwanashe Mabhaudhi, (Under review). Assessing the capabilities of drones in detecting and mapping water levels in small water bodies using machine learning techniques. Physics and Chemistry of the Earth, Parts A/B/C (Manuscript ID: JPCE-D-26-0053)

**Abstract**

Effective inland water resource management relies on accurate monitoring of spatial and temporal trends in small reservoirs. However, data scarcity remains a significant limitation. This study assesses the potential of UAV-acquired LiDAR and multispectral sensor data, integrated with robust machine learning techniques, to quantify seasonal variations in water levels and surface area. Random Forest and Extreme Gradient Boosting (XGBoost) were comparatively used in conjunction with the LiDAR-derived as well as the Normalised Difference Water Index (NDWI) to predict seasonal water levels and surface extent. The models were validated using in situ water depth measurements collected with a dip stick, alongside a boat and a handheld GeoXH 6000 receiver. These datasets were acquired concurrently during two field campaigns conducted in late autumn (May) and late spring (October) 2025. The RF model outperformed XGBoost and exhibited an RMSE value of 0.12 m in May and 0.11 m in October, with corresponding mean absolute percentage errors (MAPE) of 1.36% and 1.14%, respectively. XGBoost yielded a lower accuracy RMSE of 0.13 m and 0.13 m, and MAPE of 1.57% and 1.39% for May and October, respectively. The Random Forest model predicted minimum water levels of 1.60 m in May and 1.75 m in October, with corresponding maximum levels of 3.50 m and 3.75 m, respectively. Meanwhile, XGBoost model predicted minimum water levels of 1.65 m in May and 1.80 m in October, with corresponding maximum levels of 3.45 m and 3.72 m, respectively. The study demonstrates the feasibility of using UAV-based observations to detect and map water levels in small reservoirs. This integrated approach enhances the accuracy of water-level assessment and offers significant potential for advancing hydrological monitoring and resource management.

**Keywords**: Random Forest, Extreme Gradient Boosting, UAVs, spatiotemporal changes, reservoir.

### 3.1 Introduction

Freshwater systems, including rivers, lakes, and dams, play a crucial role in supporting biodiversity, agriculture, and socioeconomic development (Lee et al., 2022; Liu et al., 2025; Wang et al., 2025). However, increasing anthropogenic pressures on land resources, combined with climate change, are leading to significant fluctuations in water quantity and quality within these systems (Szostak et al., 2024; Yang et al., 2022). These disruptions can reduce drought prediction accuracy, increase sedimentation, heighten flood risk and water shortages (Wienhold et al., 2023). Consequently, monitoring small water bodies is essential for understanding their localised responses to environmental change and for supporting informed, site-specific water-resource management and planning decisions.

Small water bodies play a crucial role in local hydrological regulation, irrigation supply, and ecosystem services, yet their water-level dynamics remain poorly monitored due to their size and spatial heterogeneity. Effective management of small water bodies ranging from 0.01 $km^2$ to 1 $km^2$ requires continuous and accurate monitoring of hydrological parameters, particularly water extent and level dynamics (Ridolfi & Manciola, 2018; Wang et al., 2025). Conventional water level monitoring approaches, including ground-based measurements, satellite remote sensing, and hydrological modelling, have notable limitations (Acharya et al., 2021). For instance, small water bodies are often located in areas with no gauging stations (Jiang et al, 2020) and limited accessibility, due to growing private ownership of land and water resources (Zhou et al., 2025b). Ground instruments such as level loggers and staff gauges provide precise point-based data but lack spatial context and are costly to maintain across multiple sites. Remote sensing techniques for water level monitoring have gained widespread adoption, offering real-time capability, broad spatial coverage, high precision and cost-effectiveness, advantages often unavailable with traditional field methods (Mudiyanselage et al., 2022; Najar et al., 2022; Zhou et al., 2023). Although satellite platforms such as Landsat 8/9, Sentinel-2, ICESat-2, and MODIS offer broad spatial coverage, they remain limited because of their coarse spatial resolution, long revisit intervals, and their susceptibility to atmospheric interference (Billson et al., 2023; Guo et al., 2021; Hameed et al., 2022). Consequently, these systems often fail to capture the short-term dynamics and small-scale variability of water bodies that are critical for local water management and ecological assessment (Bauer-Gottwein et al., 2024; Mohamad et al., 2019).

The emergence of Unmanned Aerial Vehicles (UAVs) has revolutionised water level monitoring by offering flexible, high-resolution, and cost-effective alternatives to conventional observation systems (Giulietti et al., 2022; Kageyama et al., 2016; Ridolfi & Manciola, 2018). UAVs can operate under cloud cover, revisit sites frequently, and capture real-time data from customisable flight paths, making them ideal for high spatial and temporal resolution mapping in small basins and reservoirs. (Agrafiotis et al., 2019; Bandini et al., 2023; Lee et al., 2022; Rossi et al., 2020; Zhan et al., 2022). UAV-based sensors that have been utilised in mapping water levels in small water bodies are classified into two types: optical/visible and microwave systems (Vélez-Nicolás et al., 2021). Optical sensors, such as multispectral, hyperspectral, RGB cameras, and LiDAR, capture reflected light or laser returns to delineate water extent, generate high-resolution surface water models, and identify shoreline boundaries (Albayati et al., 2024; Hameed et al., 2022; Jiang et al., 2023). These systems are particularly effective in clear-sky conditions, providing detailed spatial information that makes them well-suited for mapping shallow water bodies with high precision (Bandini, 2017; Casas-Mulet et al., 2020; Dietrich, 2017). Microwave systems, which include radar altimeters and synthetic aperture radar (SAR) mounted on UAV platforms, actively emit and receive electromagnetic signals, enabling water-level detection even under cloud cover, at night, or in turbid or vegetated environments where optical sensors may struggle (Bandini,  et al., 2017b; Ichikawa et al., 2019; Lahmeri et al., 2025). Together, these two sensor categories provide complementary strengths for accurate, high-resolution water-level monitoring in complex and dynamic small-reservoir environments.

UAV-derived data products generated from remote sensors have greatly enhanced the capacity to observe and quantify water extent and levels in small reservoirs. Multispectral imagery enables the extraction of water extent using spectral indices such as Normalised Difference Water Index (NDWI) and Modified Normalised Difference Water Index (MNDWI), which distinguish water from surrounding land features with high accuracy (Gafurov et al., 2024; Kaya et al., 2023; Lee et al., 2022). Similarly, structure-from-motion (SfM) photogrammetry and LiDAR data allow the creation of high-resolution digital elevation models (DEMs) and water-surface elevation maps, providing detailed spatial information on shoreline positions, water-level fluctuations, and reservoir morphology. For instance, Massuel et al. (2022) utilised UAV-derived SfM DEMs to determine the water levels in Hoshas, a reservoir in Central Tunisia. In a similar study, Zhou et al. (2025b) mapped water surface elevations along a 10 km section of the Ronne River, in Sweden, using a DJI Zenmuse L1 and two radar sensors (Geolux

LX-80 (LX80) and IWR1443), achieving accuracies of 1.5–3 cm. Generally, these datasets offer unprecedented spatial and temporal resolution compared to traditional ground measurements or satellite observations, making UAV-based monitoring particularly suitable for capturing rapid hydrological changes, seasonal variations, and localised water-level dynamics (Rossi et al., 2020; Slocum et al., 2020; Zhou et al., 2025). Consequently, UAV-derived products provide a robust and scalable approach for enhancing water-resource and environmentally heterogeneous catchments.

The increasing availability of high-resolution UAV-derived datasets has also stimulated the integration of machine-learning techniques to enhance the estimation and prediction of water levels in heterogeneous small water bodies. Machine learning algorithms, including artificial neural network (ANN) He et al. (2022), support vector machine (SVR) Liu et al. (2025), decision tree (DT) Gafurov et al. (2024), convolutional neural network/s (CNNs) Kim et al. (2019), Szostak et al. (2023), have demonstrated robustness in predicting water levels and depths. These models can effectively fuse multiple UAV-derived variables, reduce classification uncertainty, and improve water-level estimation accuracy under diverse environmental conditions (Emanuele et al., 2020; Kujawa et al., 2025). In addition, machine learning approaches enable the development of predictive models that generalise across time and space, providing insights into temporal dynamics and enabling early detection of hydrological changes (He et al., 2024; Szostak et al., 2023; Yang et al., 2022). As a result, the integration of UAV remote sensing and machine learning offers a powerful framework for advancing water-level monitoring in complex and data-limited small reservoir systems. For instance, Gafurov et al. (2024), applied multiple machine learning algorithms, including random forest (RF), gradient boosting (GB) and decision tree (DT) and multispectral UAV-derived data to predict water depths in Kuibyshev Reservoir, Russia. The Decision Tree Regressor achieved the highest accuracy (RMSE = 1.92 m), highlighting the strength of tree-based models in capturing complex, non-linear environmental relationships. However, accuracy declined for depths beyond 2 m, likely due to limited light penetration.

Despite these advances, several critical gaps remain, particularly in the context of small and spatially heterogeneous water bodies. Most existing studies focus on large lakes or wide river systems, with limited attention given to small reservoirs that experience rapid hydrological fluctuations and are often excluded from formal monitoring networks. Furthermore, many UAV-based assessments rely heavily on GNSS-derived orthometric heights for validation but rarely evaluate the capability of UAV data to detect fine-scale spatiotemporal water-level variations independently. Similarly, although machine-learning models have demonstrated promising results, few studies have rigorously examined their predictive ability when applied specifically to UAV-derived multispectral and elevation datasets in small reservoir environments. These gaps are especially pronounced in the Global South, where monitoring infrastructure is limited and hydrological variability is high. Therefore, this study seeks to address these challenges by assessing the spatial and temporal capabilities of UAV-derived multispectral imagery and LiDAR-based water-surface elevation models for detecting and mapping water-level dynamics in small water bodies. Additionally, it comparatively evaluates the performance of Random Forest and Extreme and Gradient Boosting (XGBoost) algorithms in predicting seasonal spatiotemporal water-level changes at the High Down Stud Farm Dam

## 3.2 Materials and methods

### 3.2.1 Study area

The study was conducted at a small reservoir at High Down Stud Farm in Fort Nottingham, within the Umgeni catchment (-29.464610°, 29.917877°) (Figure 3.1). The dam has an approximate water depth of 4 m. It is located on generally flat terrain, with localised steep slopes ranging from 10° to 20°. The Umgeni Catchment is a hydrologically important system in KwaZulu-Natal, characterised by diverse topography, variable rainfall regimes, and intensive land and water use pressures (Hughes et al., 2018). The catchment has moderate annual temperature fluctuations (3°C-28°C) and receives annual rainfall ranging between 410 and 1450 mm during the wet season (October to April), influenced by the Agulhas Current that passes through Durban, blowing towards the southern coast tip of South Africa (Gutsa et al., 2024; Ramillien et al., 2014). A pronounced dry season starts from May to September, with precipitation dropping to as low as 2 mm, leading to variability in reservoir water levels (www.SouthAfricaWeatherService.com). The region's stable thermal regime, combined with this distinctive precipitation pattern, creates unique hydrological dynamics, making water resource management particularly crucial for both economic and ecological sustainability.

Water stored in small water bodies, sustains approximately 4 million residents and underpin 65% of the province's economic activity, including 20% of South Africa's GDP, particularly within the Pietermaritzburg-Durban economic corridor (Jojozi et al., 2025; Kahinda et al., 2022; Singh, 2023).

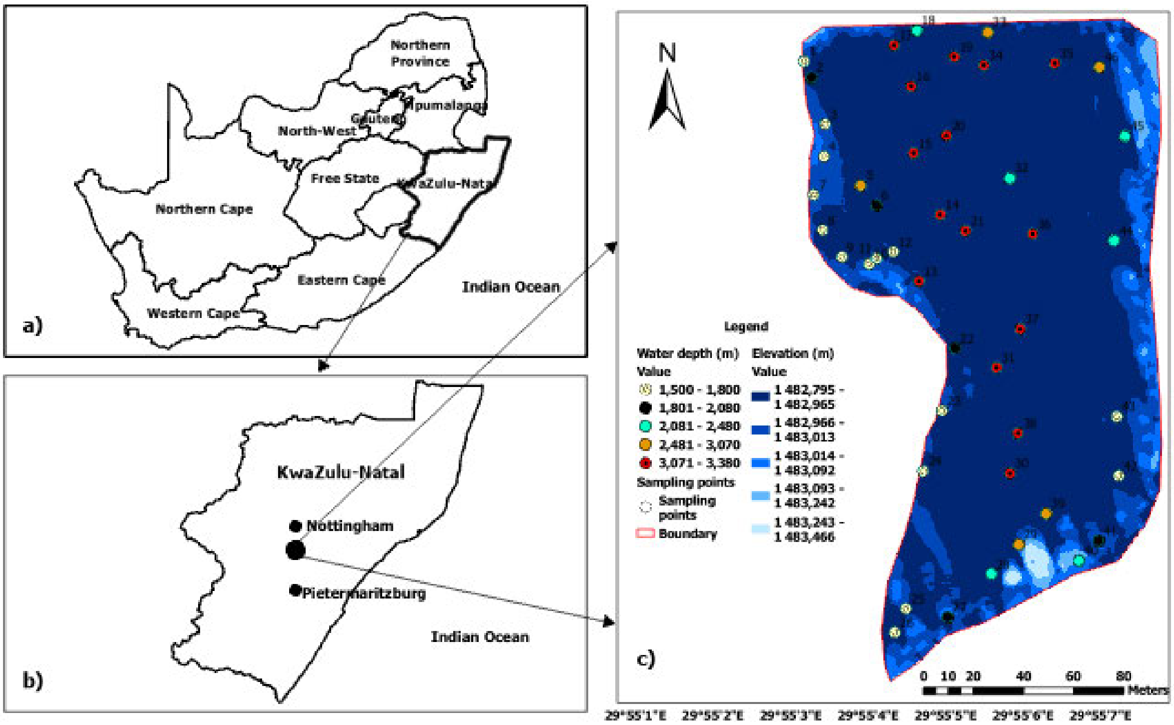



Figure 3.9**.** Study area location: South Africa (a), High Down Stud Farm Dam within KwaZulu-Natal Province (b), and High Down Stud Farm dam and sampling points in Nottingham (c).

### 3.2.2 Data collection and processing

UAV multispectral imagery, LiDAR data, and in situ water depth measurements were collected concurrently during two field campaigns conducted late autumn in May and late spring in October 2025, under clear-sky conditions and minimal wind speeds. Flights were conducted between 10:00 and 14:00 local time at an altitude of 90 m to ensure optimal solar irradiance and minimise illumination variability. Water-surface conditions during data acquisition were characterised by minimal wave activity, reducing uncertainties associated with surface roughness and specular reflection. The selected survey periods correspond to contrasting hydrological conditions, with May representing the late dry season when rainfall is minimal and October marking the onset of increasing rainfall. This, therefore, justifies the selection of May and October as acquisition dates for both field and remotely sensed data.

#### 3.2.2.1 In situ data

The shape file of the study area was digitised in Google Earth Pro. The polygon was imported into QGIS 3.42.1, where it was used to generate a systematic grid of sampling points and associated coordinates (Figure 3.1). These coordinates were uploaded to a handheld GeoXH 6000 receiver with accuracy <100 cm. A boat was deployed to access predetermined sampling locations across the reservoir (Figure 2c). The ground sampling distance (GSD) was optimised based on the spatial extent of High Down Stud Dam, and the planned UAV flight altitude. This approach captured cross-sectional variability while maintaining operational efficiency.

In situ water-level measurements were collected to calibrate and independently validate UAV-derived water-level estimates across the reservoir. Water level measurements were obtained using a calibrated dipstick (Figure 3.2c) at geocoded sampling points. At each sampling point, precise GPS coordinates were recorded at 90-second occupation time, yielding an estimated positional accuracy of ±1 cm in the horizontal ±3 cm in the vertical, together with associated standard deviation and time stamp metadata (Wienhold et al., 2023). The corresponding *X* and *Y* coordinates and measured water depths were logged in a standardised spreadsheet. A total of 46 sampling points were collected, providing comprehensive spatial coverage of the reservoir.

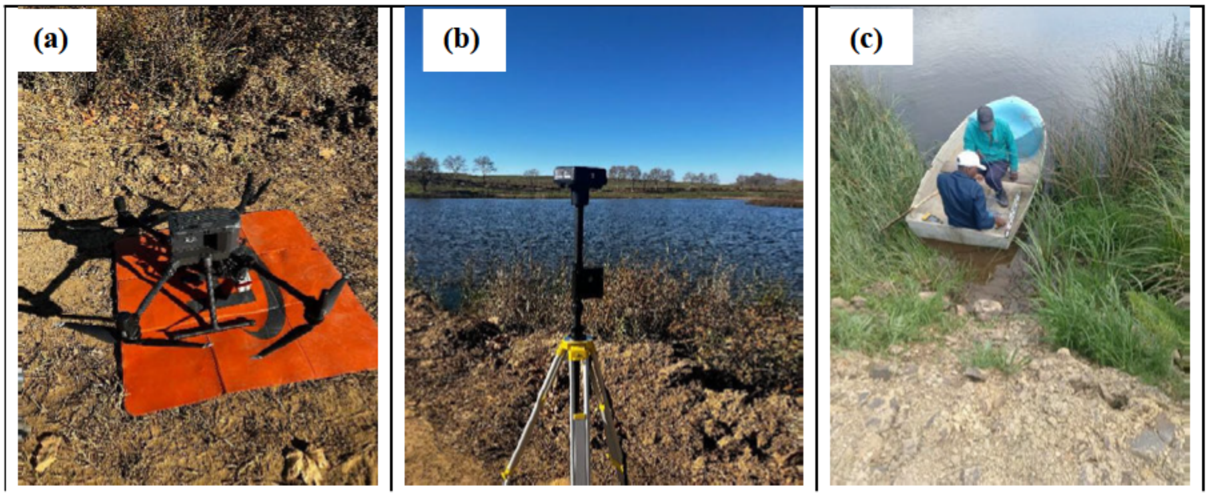



Figure 3.10. Research instruments: DJI 300 Matrice (a); Ground control station (b); Boat, calibrated dipstick and GPS (c).

#### 3.2.2.2 UAV data acquisition

The DJI Matrice 300 series (M300) onboard the MicaSense Altum multispectral camera and Livox LiDAR was used in this study (Figure 3.2a). The MicaSense Altum is a multispectral and thermal-imaging sensor with five narrow spectral bands (blue, green, red, red-edge, and near-infrared) and a long-wave infrared band. Its spectral range covers the visible spectrum (400–700 nm) and extends into the near-infrared (NIR) region (up to 1000 nm) (Gafurov et al., 2024). The camera has a sensor resolution of approximately 2064 × 1544 pixels (3.2 megapixels per multispectral band) at 90 m altitude, delivering a (GSD) of 5.2 cm per pixel (Wang et al., 2025). Additionally, the camera boasts a 48° × 37° field of view (FOV) with an 8 mm focal length (Ngo et al., 2025).

The DJI Zenmuse Livox LiDAR sensor can detect objects at ranges of 450 m under conditions of 80% reflectivity and 0 kilolux (klx) illumination, and up to 190 meters at 10% reflectivity and 100 klx. The system operates at a point-acquisition rate of up to 240,000 points per second (pts/s) in single return mode. The sensor integrates a Livox solid-state Lidar module, GNSS receiver, an inertial measurement unit (IMU), and a 20 MP camera featuring a 1-inch 178 complementary metal oxide semiconductor (CMOS) sensor. All components are mounted on a stabilised three-axis gimbal, enabling the acquisition of real-time three-dimensional point cloud data.

Radiometric calibration of the MicaSense Altum sensor was performed before each flight using a white reference calibration panel (Cao et al., 2021). Image acquisition was conducted with both forward and side overlaps set to 80%, in accordance with DJI flight-planning specifications. Return mode was set as triple, sampling rate was set at 160KHz, and scanning mode was set as repetitive. LiDAR data were collected in triple-return mode, with a sampling rate of 160kHz and a repetitive scanning pattern. The UAV flight mission followed a simple grid pattern, with flight lines spaced 4 to 6 meters. The flight took approximately 43 minutes. The drone's flight speed was predetermined to ensure optimal image overlap and data quality.

### 3.2.3 Data processing for spatial and temporal water levels monitoring

The in-situ and UAV data sets were collected and processed in accordance with the analytical framework (Figure 3.3). The captured multispectral datasets were first orthorectified, and all overlapping images were stitched together to create a single composite orthomosaic. Using Pix4Dmapper software (https://www.pix4d.com/) Kvile et al. (2024), the orthomosaic was georeferenced by assigning real-world coordinates to each pixel. These orthomosaic preserve spatial resolution and enable pixel spectral index analysis (Kujawa et al., 2025).

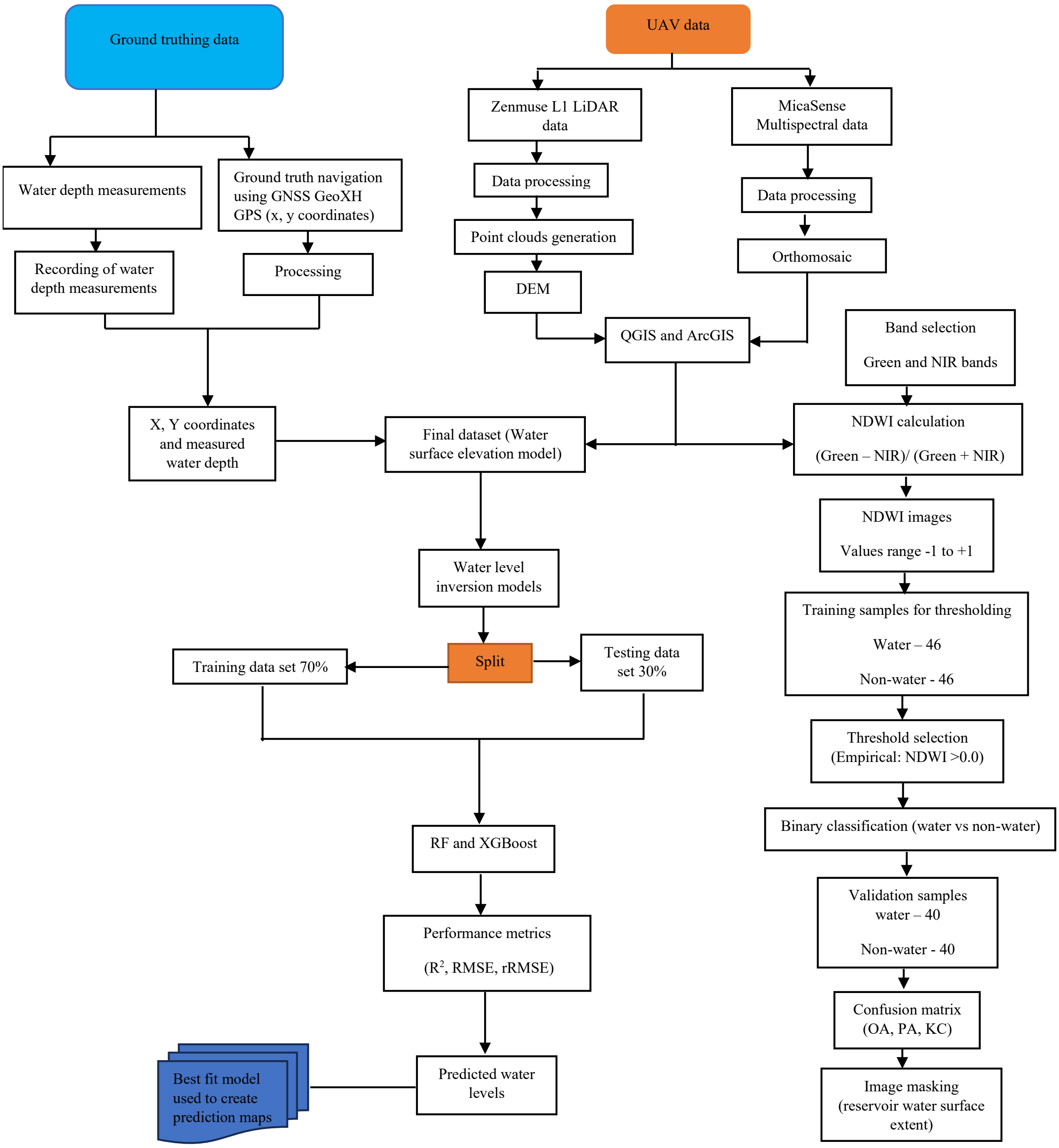



Figure 3.11. In situ and UAV workflow for data acquisition, processing and analysis.

### 3.2.4 Delineation of water surface using spectral water indices

The NDWI was used to delineate water surface extent using UAV-derived multispectral images. NDWI was selected in this study due to its robustness in delineating water surface extent, leveraging the spectral bands available from the MicaSense multispectral sensor (Kaya et al., 2023; Lee et al., 2022). The NDWI was developed by McFeeters (1996) and it uses the green and near-infrared (NIR) bands. NDWI has values that range from -1 to 1, and a threshold of 0 was used to extract water from indexed images (Bangira et al., 2019; Carballido, 2023; Xu, 2006).

### 3.2.5 LiDAR data processing

The LiDAR datasets were processed following six steps: (i) LiDAR point cloud trajectory, (ii) mission and alignment, (iii) strip adjustment, point cloud denoising, (iv) LiDAR data normalisation, (v) classification to create digital elevation model (DEM) and (vi) quality assurance using georeferenced field images (Zhou et al., 2023). Dà-Jiāng Innovations (DJI) Terra software was used to process LiDAR point-cloud data together with corresponding GNSS/RTK and IMU trajectory information, ensuring accurate spatial registration of the datasets. Strip alignment was refined using an iterative closest point (ICP) approach, and outliers were removed to reduce noise and improve data quality. Automatic point classification was applied to separate ground, vegetation, built structures, and outliers, followed by progressive triangulated irregular network (TIN) densification to refine ground returns. Ground-classified points were interpolated using TIN-based surface modelling and minimum-elevation rasterisation to generate a Geotiff DEM for water surface elevation extraction. The final water surface elevation model was validated against in-situ measurements, with interpolation accuracy dependent on point density and the model's resolution.

### 3.2.6 Estimation of dynamic water surface elevation

Water surface elevation models were used to quantify spatial and temporal variations in water levels. Water surface elevation (WSE) was estimated by extracting elevation values along the land–water boundary of the reservoir water surface elevation models. Points were generated along the water's edge using the 'Generate Points Along Lines' tool in ArcGIS Pro 3.3, and the water surface elevation models (sampled at 0.24 m resolution) were extracted. The mean and standard deviation of elevations within a buffered land–water boundary was computed using 'Zonal Statistics as Table', and the mean elevation was adopted as the representative WSE.

Model validation was performed by extracting WSE values at ground-truth water depth locations using the 'Add Surface Information' tool, which yielded a standard deviation of zero, confirming a stable and level reservoir surface. All imagery shared a uniform ground sampling distance with zero rotation effects. The estimated mean WSEs were 1483.1 m in May and 1483.4 m in October, from which the bathymetric extent of the reservoir was delineated.

### 3.2.7 Machine learning application in predicting water depth in small water bodies

In this study, Random Forest (RF) and Extreme Gradient Boosting (XGBoost) were employed to predict water depths using ground-truth measurements (Figure 3.3). Random Forest and XGBoost were selected due to their strong ability to model complex, non-linear relationships common in UAV-derived data, their robustness to noise and multicollinearity, and their capacity to handle high-dimensional datasets from LiDAR and multispectral sensors. Additionally, in the few studies where they have been applied, both models demonstrate high predictive accuracy for water level estimation in small reservoirs while requiring minimal preprocessing. Random Forest (RF) represents an ensemble machine learning approach that aggregates multiple decision tree regressors (Bangira et al., 2019; Breiman, 2001; Pal, 2005). The algorithm operates through parallel training of numerous decision trees, each utilising identical feature sets, but distinct training subsets generated via bootstrap sampling from the original dataset (Mutanga et al., 2012). When conducting the regression, individual trees independently predict class labels for test instances, with the final regression determined through majority voting across the ensemble (Gao et al., 2022; Liaw & Wiener, 2002; Zhou, 2025).

The model's performance depends critically on two key hyperparameters: tree depth which controls model complexity and minimum sample size which governs node splitting criteria. Hyperparameter tuning for the Random Forest model was conducted using random search by testing combinations of parameters, including the number of trees set to 100, 200, and 300, which determines how many decision trees are built. The maximum depth was set to None, 5, 10, and 15 to limit how deep each tree can grow, while the number of features was set to square root and algorithm base 2 (sqrt and log2) to determine the features considered at each split. The minimum samples required to split a node were defined as 2, 5, and 10, and the minimum samples per leaf were set to 1, 2, and 4. In this study, pruning harshness was set to 51 to control tree complexity and prevent overfitting, as suggested by (Liu et al., 2025). Random forest is very robust to missing data and unbalanced data, and can predict well the results of up to thousands of explanatory variables (He et al., 2023; Iverson et al., 2008; Saeidi et al., 2023).

Meanwhile, Extreme gradient boosting (XGBoost) was selected for its strong predictive capability, robust handling of missing values, and integrated least absolute shrinkage and selection operator (LASSO) (L1) and ridge (L2) regularisation mechanisms, which effectively mitigate model complexity (Gafurov et al., 2024; Liu et al., 2025). Its capacity to efficiently process both small and large datasets through parallel computation has established XGBoost as a widely preferred algorithm for spatiotemporal water levels mapping and validation of small reservoirs (Liu et al., 2025). The algorithm builds trees iteratively to achieve feature splitting, with each tree containing multiple leaf nodes, and each leaf node representing a score. The prediction is obtained by summing the scores from all the trees. Hyperparameter tuning for the XGBoost model was conducted using random search, testing combinations of key parameters, including the number of trees (total boosting rounds) set to 100, 200, and 300. The maximum depth was set to values of 3, 5, and 7 to limit tree complexity and prevent overfitting. The learning rate was assigned values of 0.01, 0.1, and 0.2 to control how quickly the model learns and to improve generalization, while the subsample parameter, representing the fraction of training data used per tree, was set to 0.7, 0.8, and 1.0.

### 3.2.8 Training and predicting samples

The measured water-depth was used as training data. Each model was trained and evaluated in Python Jupyter Notebook. The maximum number of samples class was 46. The dataset was split into training and testing sets using a 70:30% ratio, resulting in 32 training samples and 14 testing samples, ensuring a robust evaluation framework (Figure 3.3). The training data were subjected to 5-fold cross-validation, where each fold used approximately 25 samples for training and 7 for validation. The optimal parameter set was selected based on cross-validation performance, typically using $R^2$ metric, and the final model was then evaluated on the 14 test samples to assess its generalization capability. Python Jupyter Notebook facilitated efficient parallelisation of the computations. The results were visualised using bar plots of $R^2$ and RMSE, along with scatter plots comparing observed and predicted water depth for the best-performing model. This comprehensive approach ensured a detailed understanding of the predictive capabilities of RF and XGBoost in estimating water depth.

### 3.2.9 Accuracy assessment

The binary images were validated with the ground truth map. The sampling strategy chosen was stratified random sampling, and a total of forty-six sampling points were selected for assessment. After ground truthing the binary images, a confusion matrix was processed using the ‘compute confusion matrix’ function chosen in geoprocessing.

A producer’s accuracy (PA), overall accuracy (OA), and the Kappa Coefficient (K) were generated. The Overall Accuracy (OA) and Kappa Coefficient (K), calculated through (Equation 1) and (Equation 2), to evaluate the accuracy of the extraction results. OA is easily interpreted as it represents the percentage of classified pixels in the image that have been correctly labelled. At the same time, K can be used to assess statistical differences between classifications (Ballanti et al., 2016).

$$Overall\ Accuracy\text{: } ¼(TP + TN) = T_{100}\% \qquad \text{Equation 1}$$

$Kappa\ Coefficient$: Equation 2

$$= \frac{2(TP\ x\ TN - FNxFP)}{(TP + FP)x(FP + TN)x(TP + FN)x(FN + TN)}$$

where TP (True Positive) and TN (True Negative), represent water and non-water pixels/points that match the reference points, while FP (False Positive) and FN (False Negative) refer to those pixels/points that are discrepant with the reference sites.

Differences considered statistically significant at $p < 0.05$. The first statistical indicator is the coefficient of determination ($R^2$) in, which explains the variance score of a regression model.

Furthermore, model performance was evaluated using the mean absolute percentage error (MAPE; Equation 3) and root-mean-square error (RMSE; Equation 4). The best-performing model was characterised by a higher coefficient of determination ($R^2$) and a lower RMSE, and MAPE indicate a better fitting performance.

$$\mathrm{MAPE} = \frac{1}{\mathrm{n}} \sum_{\mathrm{i=0}}^{\mathrm{n}} \frac{|\ \bar{\mathrm{y}}_{\mathrm{i}} - \mathrm{y}_{\mathrm{i}}\ |}{\max\ |\ (\epsilon,\ |\mathrm{y}_{\mathrm{i}}\ |)}$$ Equation 3

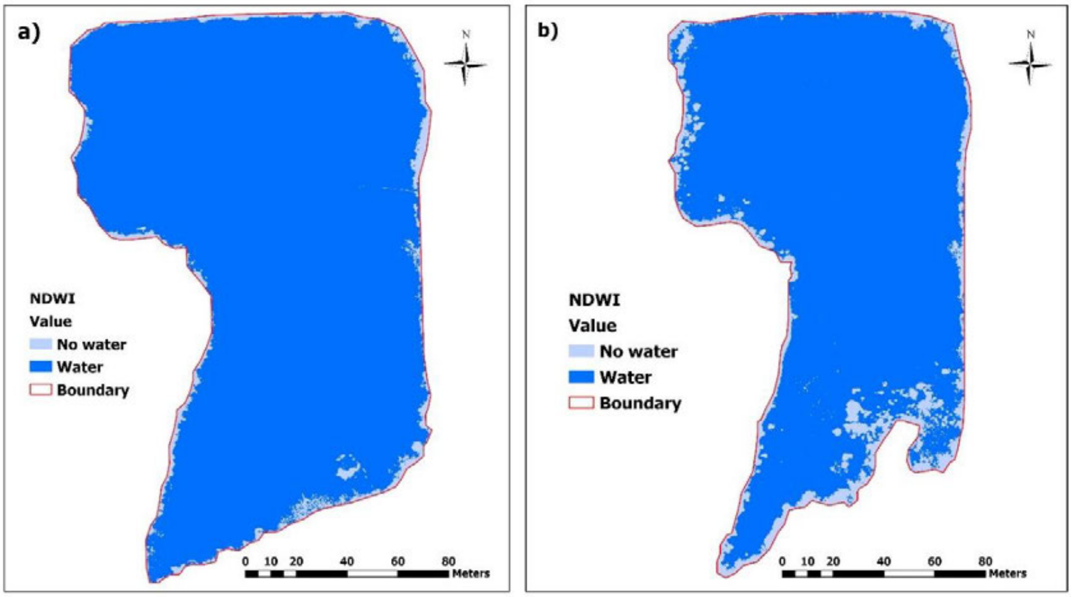
$$\mathrm{RMSE} = \frac{\sqrt{\sum^{\mathrm{n}}{}_{\mathrm{i}} = 1(\bar{\mathrm{y}}_{\mathrm{i}} - \mathrm{y})^2}}{\mathrm{n}}$$ Equation 4

Where, n is the number of sample points, $\bar{y}_i$ represents the estimated water depth, and $y_i$ represents observed water depth.

## 3.3 Results

### 3.3.1 Reservoir surface extent delineation using spectral indices.

The OA values of NDWI were 98.4.0% and 93.4% in May and October, whilst the corresponding producer accuracy values are 97.1% and 98.7%, respectively. The corresponding Kappa Coefficient values for May (Late autumn) and October (Mid to late spring) are 0.96 and 0.94, respectively. The NDWI OA and F1 score were high, thereby reducing omission errors (Figure 3.4a and Figure 3.4b). The NDWI delineated a relatively larger water surface extent in May, which subsequently contracted in October, indicating a seasonal reduction in reservoir water coverage (Figure 3.4a and Figure 3.4b). The observed reduction in reservoir water surface area from 18725.051 $m^2$ in May to 16152.950 $m^2$ in October might be attributed to growth of algae, cyanobacteria and water hyacinth (*Eichhornia crassipes*) during the late spring (Figure 3.4c).



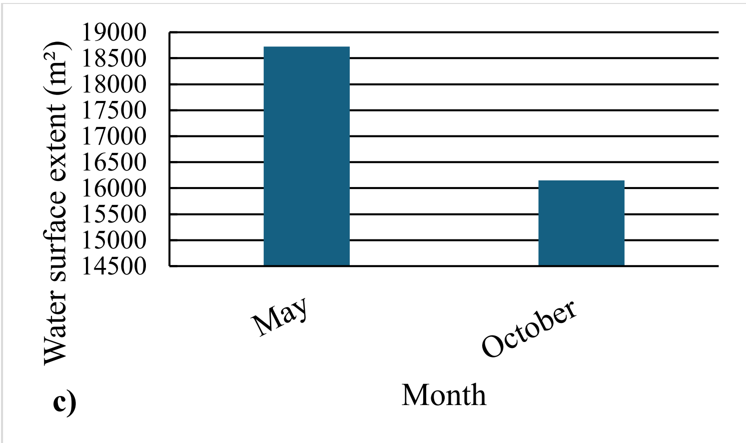




Figure 3.12

Figure 3.12. The water surface extent maps of High Down Stud Farm for May (a) and October (b), and corresponding water surface area ($m^2$) (c).

### 3.3.2 UAV-derived water surface elevation

A comparison of UAV-derived WSE models reveals distinct spatial and seasonal variations between late autumn in May and late spring in October. In May, WSE values were relatively low, with a mean elevation of 1483.4 m recorded along the reservoir water edge. A marked decline in WSE was observed with increasing distance from the water edge, where elevation values of 1483.2 m, 1483.1 m, and 1483.0 m were successively recorded. The lowest WSE values occurred in the central portion of the reservoir, with elevations decreasing further to 1482.9 m, 1482.8 m, and 1482.7 m, indicating a progressive reduction in water surface elevation toward the reservoir interior during the late autumn (Figure 3.5).

In October, the WSE exhibited a pronounced increase, with a maximum elevation of 1483.5 m recorded along the reservoir water edge. A systematic decline in WSE was observed toward the central section of the reservoir, where intermediate elevation values of 1483.4 m, and 1483.43 m were recorded. Lower WSE values, ranging from 1483.0 m to 1483.3 m, characterised the mid-reservoir zone.

Figure 3.5 shows no abrupt peaks in WSE for either May or October, suggesting that the UAV-derived WSE models were generated from UAV-derived data acquired under stable reservoir conditions and calm atmospheric settings, characterised by low wind speeds. Overall, WSE values varied between approximately 1483.2 m and 1483.3 m across the May–October period, reflecting seasonal water-level variability (Figure 3.5). In general, higher WSE values correspond to elevated reservoir stages, whereas lower WSE values indicate reduced water levels.

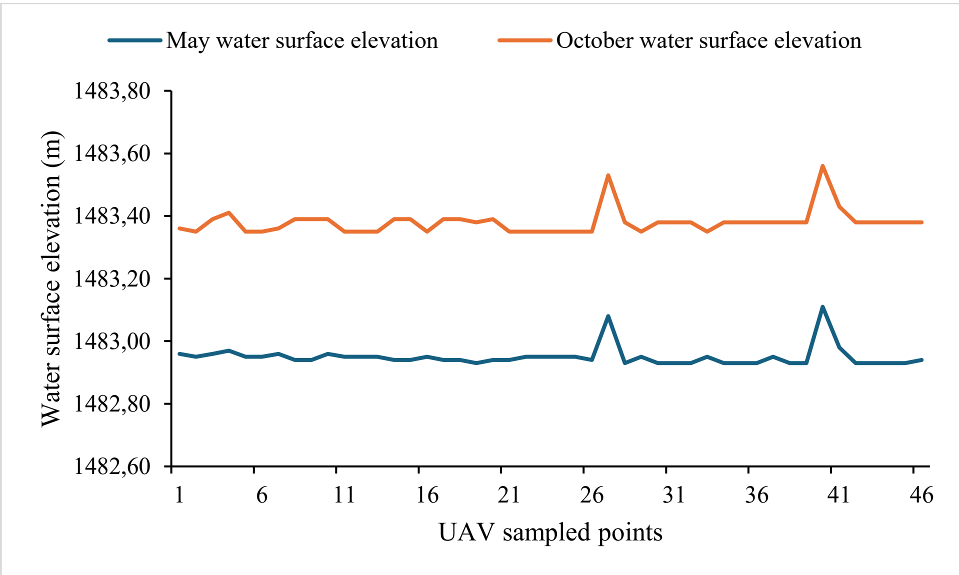


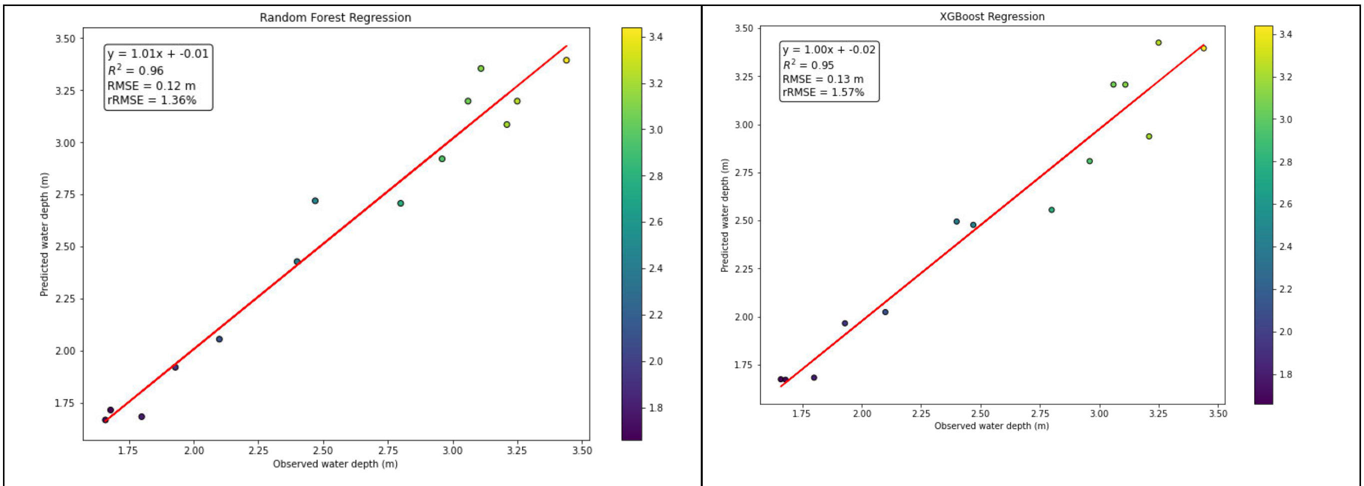

Figure 3.13. Mean water surface elevation for May and October.

### 3.3.3 Performance evaluation of machine learning approaches in predicting water depth

Figure 3.6 shows the accuracy evaluation and error statistics from Random Forest (RF) and Extreme Gradient Boosting (XGBoost) models. The Random Forest model, RMSE and rRMSE values were slightly higher in May and lower in October. Meanwhile, the corresponding XGBoost model RMSE and rRMSE values were higher than RF model values in May and October respectively. The RF obtained higher $R^2$ values than XGBoost in May and October respectively, reflecting its robustness.

In May, the Random Forest (RF) model exhibited strong predictive capability, attaining an $R^2$ of 0.96, an RMSE of 0.12 m, and a rRMSE of 1.36% (Figure 3.6a). In comparison, the XGBoost model showed comparatively slightly lower accuracy, with an $R^2$ of 0.95, an RMSE of 0.13 m, and an rRMSE of 1.57% (Figure 3.6b). In October, RF consistently outperformed XGBoost, achieving an $R^2$ of 0.97, an RMSE of 0.11 m, and an rRMSE of 1.14% (Figure 3.6c). Although XGBoost also performed well during this period, it produced slightly reduced accuracy metrics, with an $R^2$ of 0.96, an MAE of 0.11, an RMSE of 0.13 m, and an rRMSE of 1.39% (Figure 3.6d). Overall, RF attained the highest predictive accuracy.

The scatter plots show a clear clustering of points along the 1:1 line, demonstrating good agreement between predicted and measured depths. Model predictions remained robust in areas excluded from calibration, suggesting strong generalisation capability. Analysis of the fitted regression lines reveals a systematic tendency for depth overestimation in shallow areas and underestimation in deeper regions, likely due to water-surface smoothing effects and reduced depth sensitivity in optically complex or deeper zones




**(a)** **(b)**

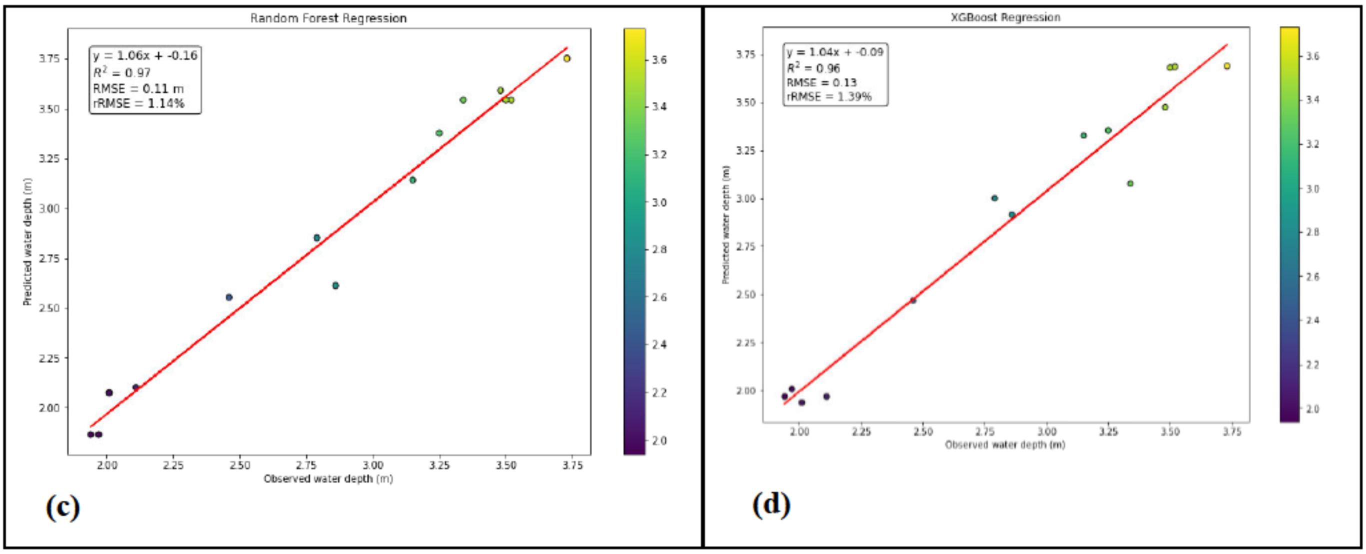



Figure 3.14. Random forest (RF) May (a), Random Forest (RF) October (c), XGBoost May (b) and XGBoost (d), scatter plots showing water depth prediction.

### 3.3.4 Error variations with depths

Error evaluation of RF models water depth estimates relative to ground-truth measurements revealed clear spatial and depth-related patterns. For May, discrepancies at sampling points 1–11, located near the land–lake boundary and associated with shallow water conditions, ranged between 0.10 and 0.35 m (Figure 3.7). In contrast, sampling points 12–46 exhibited slightly higher error values, generally between 0.15 and 0.45 m, reflecting increased uncertainty in deeper sections of the lake. An exception was sampling point 38, which, despite being positioned at the land–lake boundary, showed an error magnitude consistent with the deeper-water group (Figure 3.7).

In October, a similar trend was observed. Mean error values for sampling points 1–11 fluctuated between 0.15 and 0.45 m, indicating a modest increase in discrepancy compared with May (Figure 3.7). Error values from sampling points 12–46 were comparatively higher, varying between 0.20 and 0.50 m, further demonstrating the influence of increasing water depth on model uncertainty. Additionally, the bias of each model is generally positive, that is, the average predicted water depth is slightly higher than the reference water depth. Overall, the analysis shows a consistent pattern whereby error magnitude increases with water depth. Additionally, the bias of each model is generally positive, that is, the average predicted water depth is slightly higher than the reference water depth.

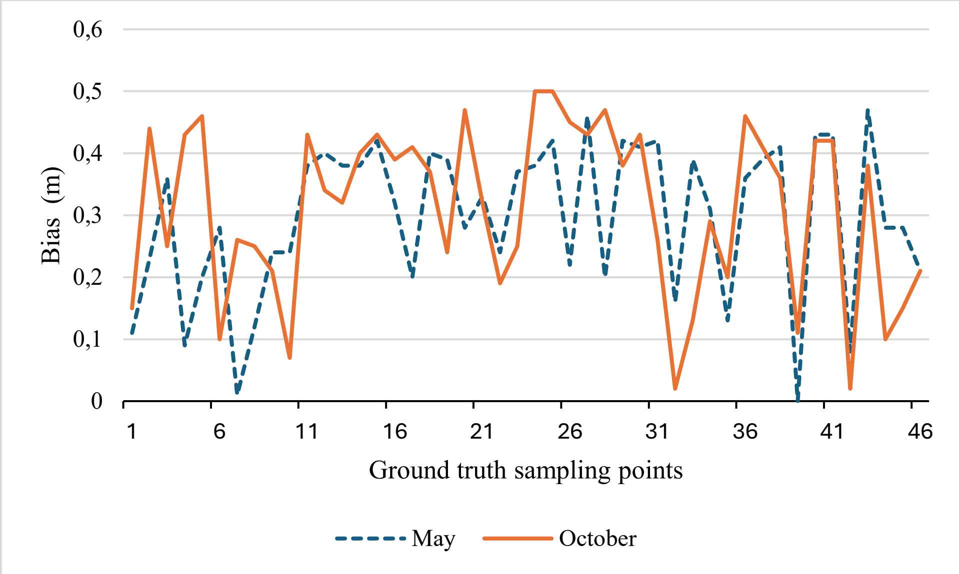



Figure 3.15. Graph showing bias between ground truth and RF derived depth for the months of May and October

### 3.3.5 Depth maps generated by the best fit machine learning algorithm

As illustrated in Figure 3.8, water depth distributions were obtained using Random Forest inversion model. The predicted water depth for the month of May ranges from 1.41 m near the land-lake boundary were relatively low, whilst depths up to 3.27 m (maximum) were recorded in low land north part of the reservoirs (Figure 3.8a). The central part of the reservoir attained an average mean depth of approximately 2.47 m. Random Forest water depth attained a standard deviation of 0.56 m from mean and maximum depths. In October, water depths ranged from as 1ow as 1.54 m (near water-land boundary), whilst the maximum depth of 3.43 m was predominantly recorded in the northern parts of the reservoir (Figure 3.8b). The average mean depths of approximately 2.73 m were predominantly recorded in the south and west parts of the reservoir (Figure 3.8b). Overall, the random forest managed to predict water level fluctuations between late autumn in May and mid to late spring in October, with low water levels recorded in May, whilst the highest water levels were recorded in October.

As observed, water depth gradually increased from the northwest and southwest towards the central and north-eastern regions of the lake. The depth of most areas was less than 3.5 m and the deepest was in the centre of the lake. Notable differences were observed in regions where water depths exceeded 3.4 m (Figure 3.8b). Overall, the predicted values from both models demonstrated a high agreement with the measured observations, closely tracking their fluctuations and exhibiting only negligible errors, thereby underscoring the robustness of the model.

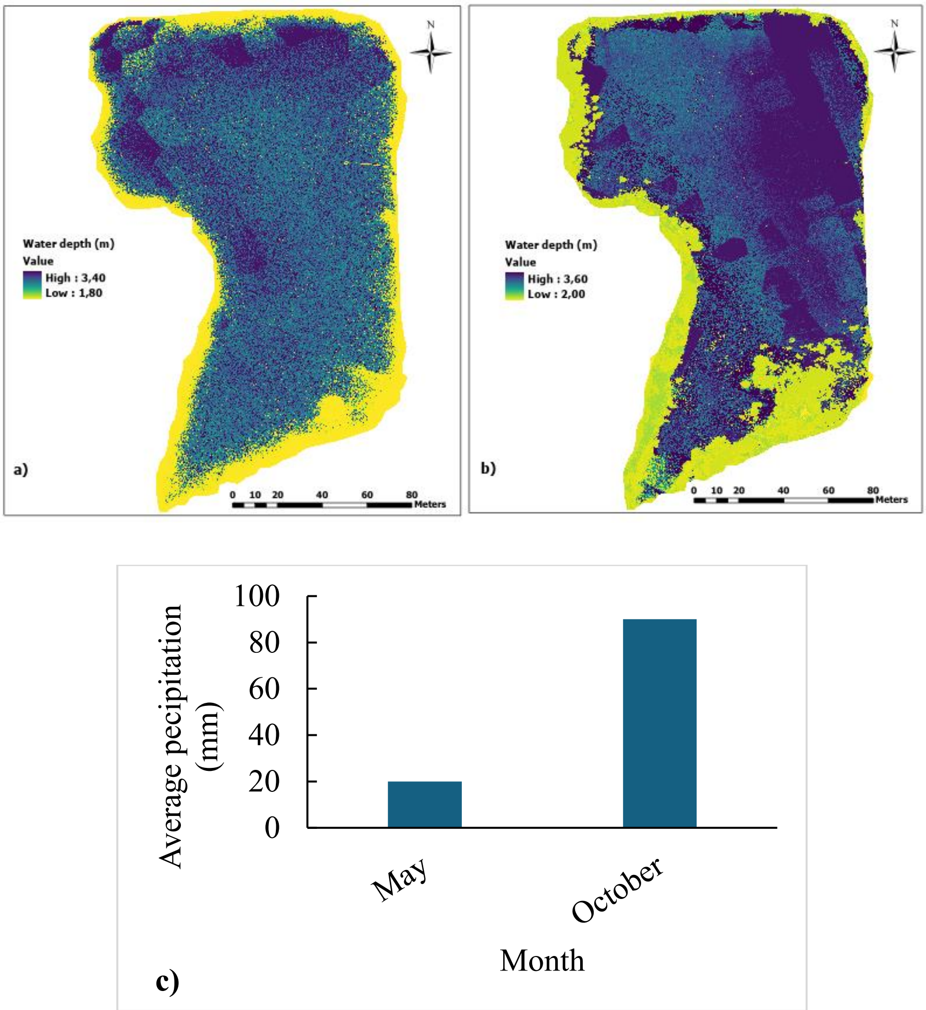



Figure 3.16. Water depth maps of High Down Stud Farm dam based on Random Forest, May (a) and October (b), and average precipitation for May and October (c).

## 3.4 Discussion

The main objective of this study was to assess the spatial and temporal capabilities of UAV-derived multispectral imagery and LiDAR-based water-surface elevation models for detecting and mapping water-level dynamics in small water bodies. Additionally, it comparatively evaluated the performance of Random Forest and Extreme and Gradient Boosting (XGBoost) algorithms in predicting seasonal spatiotemporal water-level changes at the High Down Stud Farm Dam.

### 3.4.1 Spatiotemporal changes of water levels in small water bodies

The spatiotemporal analysis revealed clear patterns of water level variability in small water bodies, highlighting both seasonal trends and short-term fluctuations. The results indicated that water levels were low in the dry season, with minimum and maximum water depth of approximately 1.41 m and 3.27 m in May and fluctuated during the wet season, with minimum and maximum ground truth water depth of 1.54 m and 3.43 m recorded in October (Figure 3.8a and Figure 3.8b). The UAV-derived water depth estimates exhibited a consistent tendency to underestimate observed water depths by negligible 0.35 m and 0.4 m in May and October, respectively (Figure 3.7). The study finds that an increase in WSE indicates an increase in depth and water levels, and the reverse is true. The estimated water level values demonstrate strong consistency with field measurements, as the maximum error at each measured depth is substantially lower than the 0.5 m sensitivity threshold (Figure 3.7), typically considered critical in hydraulic models such as HEC-RAS (Ridolfi et al., 2014). This underscores the potential of UAV-derived geospatial data for quantifying spatial and temporal variability in water-level estimates in small reservoirs. The changes in water levels can be used in flood modelling as well as predicting drought.

The results indicate that spatial and temporal variations in water levels at the High Down Stud Farm Dam were predominantly influenced by variations in precipitation patterns. This is in line with the findings of He et al. (2021), who reported that seasonal and interannual variability in precipitation regimes resulted in spatial and temporal water-level fluctuations ranging from 15 m to 17 m at Spark Lake, China, as derived from UAV-based RGB imagery and photogrammetric analysis. Overall, the findings demonstrate the feasibility of UAV-derived data for reliably characterising spatial and temporal variations in water levels in small water bodies.

### 3.4.2 Comparative analysis of RF and XGBoost attributes in predicting water level changes in small water bodies

The results showed that RF outperformed XGBoost in estimating water surface levels in the High Down Stud Farm Daam. The observed superior performance of the Random Forest (RF) model over XGBoost in estimating water levels from UAV-remotely sensed data can be attributed to fundamental differences in their learning mechanisms and their ability to handle the characteristics of UAV-derived datasets for small reservoirs. RF, is a bagging-based ensemble algorithm, constructs multiple decision trees using bootstrap sampling and random feature selection, thereby enhancing model robustness and reducing sensitivity to noise and outliers. This property is particularly advantageous when working with LiDAR-derived elevation and intensity metrics, which are often affected by surface roughness, water-vegetation interactions, and residual errors in point cloud classification.

Furthermore, RF demonstrated a strong capacity to model nonlinear relationships between LiDAR-derived predictors and water depth, while effectively managing multicollinearity among correlated LiDAR features (Figure 3.6a and Figure 3.6c). Given the complex spatial heterogeneity of reservoir environments, RF's ability to integrate diverse LiDAR-derived variables with less rigorous hyper-parameter tuning likely contributed to its higher predictive accuracy. This aligns with findings of Rehamnia and Mahdavi-Meymand (2025), who reported RF efficiency in reservoir level predictions with a comparably low average RMSE value of 0.536 m for the three dams in Algeria: Kramis dam, Bougous dam and Fontaine Gazelles dam water level fluctuations. In the same study, RF outperformed shallow neural network, deep neural network and SVR in predicting spatiotemporal change in water levels.

In contrast, XGBoost, which employs a gradient boosting framework, is inherently more sensitive to noise and hyperparameter configuration. Although XGBoost is theoretically capable of achieving high predictive performance. This is because its sequential tree-building process can amplify the influence of noisy or misclassified LiDAR points, particularly in reservoirs characterised by complex water-land boundaries and variable surface conditions (Agrafiotis & Demir, 2025; Zhang et al., 2022). Moreover, the performance of XGBoost is strongly dependent on optimal parameter tuning, and suboptimal regularisation. In this study, the learning rate might have limited its ability to generalise across spatial and temporal variations in water levels, resulting in relatively higher RMSE values and less accurate models (Figure 3.6b and Figure 3.6d).

Overall, the results indicate that RF is more resilient to the uncertainties inherent in water level estimation, while XGBoost, despite demonstrating stable predictive performance, appears less robust under conditions of limited training data and high spatial variability. The results confirm RF as a robust model for small reservoir water level estimation and underscore the importance of algorithm selection in assessing spatial and temporal changes of water level in small reservoirs. However, both models achieved MAPE values below 5%, indicating strong predictive performance in capturing spatial and temporal variations in water levels of High Down Stud Farm dam.

### 3.4.5 Limitations and future directions

Despite the high-resolution capabilities of MicaSense multispectral imagery and Zenmuse Livox LiDAR L1, several limitations affect the accuracy of water surface extent and water level measurements. For MicaSense, spectral sensitivity is constrained to visible and near-infrared bands and lacks short-wave infrared (SWIR) which is well suited for detecting and mapping water surfaces. This fixed hardware limitation constrained the water indices we could compute. Hence, future studies should employ sensors with SWIR capabilities and explore recent advancements in edge-aware remote sensing techniques, such as Oriented Synthetic Aperture Radar (SAR) Ship Detection Based on Edge Deformable Convolution and Point Set Representation. While the Zenmuse Livox LiDAR enables accurate estimation of mean WSE, it cannot characterise subsurface water properties. Future work should incorporate hyperspectral imaging and sonar technologies to enhance water column penetration and enable direct bathymetric mapping. More so, future studies should consider the integration of Artificial Intelligence and Machine learning (AI/ML) for real-time processing, such as deep learning for noise correction in turbid waters for automated bathymetry mapping. Hybrid UAV-satellite systems for multi-scale monitoring, address gaps in temporal coverage for dynamic small reservoirs. Despite the strong performance of the RF model in capturing spatial and temporal variations in water levels, further research is required to fully explore its potential for accurate and robust prediction and optimise its predictive capability across diverse small reservoirs. The reliance on site-specific UAV data may restrict direct applicability to other regions due to variations in terrain, vegetation, climate, and water body characteristics. Future studies should test the approach across diverse environments and incorporate multi-site data and transfer learning to improve generalizability and scalability. More, whether conditions cloudy, rain and wind speed, which can affect UAVs flight efficiency limited the number of flights which we could have carried out. Future studies should incorporate hybrid systems integrating UAV data with satellite imagery with hyperspectral sensors could provide both high-resolution local monitoring and regional coverage.

### 3.3.5 Conclusion

This study sought to assess the integration of remote sensing and machine learning techniques to quantify the seasonal water level and surface extent fluctuations in small reservoirs. Based on the findings of this study it can be concluded that:

- UAV-driven LiDAR data in conjunction with machine learning techniques could accurately and effectively estimate seasonal water level fluctuations at accuracies that are substantially lower than the 0.5 m sensitivity threshold, typically considered critical in hydraulic models such as HEC-RAS

- The Random Forest model consistently outperformed XGBoost in predicting seasonal water level fluctuations in small water bodies, although both models demonstrated strong predictive performance.
- Thresholding could effectively map the surface extent covered by water in a typical farm dam.

Overall, this study highlights the potential of integrating UAV-derived data with machine learning approaches to overcome data limitations, providing accurate, high-resolution, and repeatable estimates of water levels in small reservoirs, especially in the Global South, with important implications for agricultural productivity, drought assessment, and flood risk prediction.

# Chapter Four: The Synthesis

### 4.4.1 Introduction

Small water bodies are increasingly recognised as critical components of hydrological and ecological systems, often disproportionately important despite their size, especially in the farming sector. Considering the significant role of small water bodies in irrigation, drinking water provision, flood and drought forecasting, and ecological regulation, improved methods for their monitoring, management, and systematic understanding are required (Biggs et al., 2017). In this regard, mapping spatial and temporal water levels in small water bodies has become of paramount importance to quantify water availability, thereby enabling informed decision-making for improved agricultural productivity. The advancement of earth observation facilities facilitated technologies, such as high spatial and temporal UAV-remotely sensed data and machine learning techniques has proven proficiency in providing precise water level estimates over conventional hydrometric approaches and coarse resolution of satellite-based data (Szostak et al., 2023). There is a considering the dearth in literature that attempts to engage these technologies in spatially quantifying water quantity in small reservoirs. In this regard, this study sought to assess the capability of UAV-borne multispectral and LiDAR sensors in mapping water levels in small water bodies. To address this main objective, the specific objectives were:

- To systematically review the literature on the utility of UAVs' remotely sensed data for detecting and mapping water levels of rivers and dams.
- To assess the capability of integration of UAV-borne sensors with machine learning in detecting and mapping seasonal water levels and surface extent in small water bodies.

### 4.4.2 Overview of the results

In systematically reviewing literature on the utility of UAVs' remotely sensed data for detecting and mapping water levels of rivers and dams, results indicated that there is significant progress. However, few studies have been conducted in the water-stressed Global South region, predominantly in small reservoirs. Results also demonstrated that the application of the compelling machine learning techniques, such as RF and XGBoost is still limited in detecting and mapping water levels in small water bodies using UAV- remotely sensed data. More so, there is no clear benchmark established in literature for detecting and mapping water levels in small bodies, hence necessitating intensive study. Assessing small water bodies through UAV-remote sensing extends beyond direct estimation of water levels, as it also supports more informed irrigation scheduling and enhances the capability for flood and drought assessment. This study advocates for more studies to explore the potential of UAV-remote sensing alongside with ground truthing datasets and advanced machine learning techniques, in the Global South, particularly in small reservoirs to optimise water levels prediction.

The study finds the significant contribution of RF and XGBoost comparatively used in conjunction with UAVs' LiDAR-derived data as well as the NDWI to predict seasonal water levels and surface area extent based on field dipstick measurements in High Down Stud Dam in Nottingham in KwaZulu-Natal, South Africa. The study identified the RF model as the robust approach for predicting spatial and seasonal-temporal variability in water level dynamics. However, both RF and XGBoost model prediction error was less in late autumn in May and late spring in October, suggesting robust and reliable agreement between observed and predicted water levels. The findings confirm that UAV-remotely sensed LiDAR data, when coupled with robust machine learning algorithms and UAV-derived multispectral data provide a reliable and efficient framework for mapping water levels and surface extent in small water bodies. This study addresses critical gaps in the literature, particularly the limited application of machine learning and UAV-based remote sensing for monitoring small reservoirs in the Global South region.

### 4.4.3 Conclusion

The overall study sought to assess the integration of UAV-borne sensors with machine learning in detecting and mapping water levels and surface extent in small water bodies. The first objective systematically reviewed literature on the utility of UAVs' remotely sensed data for detecting and mapping water levels of rivers and dams. Based on the findings of this study, it can be concluded that:

- Few studies have been conducted in the water-stressed Global South, particularly in small reservoirs, and the effective utilisation of advanced modelling approaches in predicting water levels is still limited.
- UAV-based LiDAR and multispectral data, coupled with machine learning techniques, provide a robust alternative by providing high-resolution, site-specific observations capable of capturing seasonal water level fluctuations and surface area extent.
- RF when fused with UAV-LiDAR remotely sensed data optimally predicts seasonal water level fluctuations in High Down Stud Farm Dam, in South Africa, when compared to the XGBoost algorithm.

- NDWI and thresholding optimally quantified the seasonal fluctuations in surface extent covered by water in the small reservoir.

The integration of UAV-remotely sensed data and advanced computer machine learning approaches in water levels prediction offers a useful path to a more effective monitoring of water levels in small water bodies, with ensemble learning approaches being well-suited for hydrological applications involving complex water-surface interactions. Collectively, these contributions advance both theoretical understanding and practical implementation of UAV-based water level monitoring and provide a better understanding of seasonal fluctuations in water levels and serve as a stepping stone towards small reservoirs' water level prediction, particularly in water-stressed countries of the Global South.

**4.4.4 Recommendations and directions for future research**

Despite the success attained by this study in extensively bridging existing gaps in literature, more research is still required to explore the full potential of these approaches in mapping water levels in small water bodies. Future studies should consider:

- Research in transfer learning and model generalisation would further enhance the scalability of machine learning approaches.
- Extensively assess the full potential of UAV-derived data together with ground-measured water depth to predict water levels in global small reservoirs.
- Evaluate the feasibility and full potential of advanced machine learning approaches in water level prediction to different hydrological contexts.
- Additionally, coupling UAV data with satellite observation could enable multi-scale monitoring frameworks that balance spatial detail with regional coverage.
- Integration of UAV multi-sensor systems, including multispectral, hyperspectral, LiDAR, radar and sonar, to complement the limitations of each sensor technology.

## References


Abdelal, Q., Al-Rawabdeh, A., Al Qudah, K., Hamarneh, C., & Abu-Jaber, N. (2021). Hydrological assessment and management implications for the ancient Nabataean flood control system in Petra, Jordan. *Journal of Hydrology*, *601*, 126583.

Acharya, B. S., Bhandari, M., Bandini, F., Pizarro, A., Perks, M., Joshi, D. R., Wang, S., Dogwiler, T., Ray, R. L., & Kharel, G. (2021). Unmanned aerial vehicles in hydrology and water management: Applications, challenges, and perspectives. *Water Resources Research*, *57*(11), e2021WR029925.

Agrafiotis, P., & Demir, B. (2025). Deep learning-based bathymetry retrieval without in-situ depths using remote sensing imagery and SfM-MVS DSMs with data gaps. *ISPRS Journal of Photogrammetry and Remote Sensing*, *225*, 341–361.

Agrafiotis, P., Skarlatos, D., Georgopoulos, A., & Karantzalos, K. (2019). Shallow water bathymetry mapping from UAV imagery based on machine learning. *arXiv preprint arXiv:1902.10733*.

Albayati, M. M. A., Al-Janabi, A. M. S., & Mahameed, A. I. (2024). Application of remote sensing and GIS techniques for monitoring water volume variations in inaccessible reservoirs. *Hydrological Sciences Journal*, *69*(15), 2312–2322.

Alvarez, L. V., Moreno, H. A., Segales, A. R., Pham, T. G., Pillar-Little, E. A., & Chilson, P. B. (2018). Merging unmanned aerial systems (UAS) imagery and echo soundings with an adaptive sampling technique for bathymetric surveys. *Remote Sensing*, *10*(9), 1362.

Ansari, E., Akhtar, M. N., Abdullah, M. N., Othman, W. A. F. W., Bakar, E. A., Hawary, A. F., & Alhady, S. S. N. (2021). Image processing of UAV imagery for river feature recognition of Kerian River, Malaysia. *Sustainability*, *13*(17), 9568.

Awadallah, M. O. M., Malmquist, C., Stickler, M., & Alfredsen, K. (2023). Quantitative evaluation of bathymetric LiDAR sensors and acquisition approaches in Lærdal River in Norway. *Remote Sensing*, *15*(1), 263.

Backes, D., Smigaj, M., Schimka, M., Zahs, V., Grznárová, A., & Scaioni, M. (2020). River morphology monitoring of a small-scale alpine riverbed using drone photogrammetry and LiDAR. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, *43*, 1017–1024.

Ballanti, L., Blesius, L., Hines, E., & Kruse, B. (2016). Tree species classification using hyperspectral imagery: A comparison of two classifiers. *Remote Sensing*, *8*(6), 445.

Bandini, F. (2017). Hydraulics and drones: observations of water level, bathymetry and water surface velocity from Unmanned Aerial Vehicles.

Bandini, F., Butts, M., Jacobsen, T. V., & Bauer-Gottwein, P. (2017a). Water level observations from unmanned aerial vehicles for improving estimates of surface water–groundwater interaction. *Hydrological Processes*, *31*(24), 4371–4383.

Bandini, F., Jakobsen, J., Olesen, D., Reyna-Gutierrez, J. A., & Bauer-Gottwein, P. (2017b). Measuring water level in rivers and lakes from lightweight Unmanned Aerial Vehicles. *Journal of Hydrology*, *548*, 237–250.

Bandini, F., Kooij, L., Mortensen, B. K., Caspersen, M. B., Thomsen, L. G., Olesen, D., & Bauer-Gottwein, P. (2023). Mapping inland water bathymetry with ground penetrating radar (GPR) on board unmanned aerial systems (UASs). *Journal of Hydrology*, *616*, 128789.

Bandini, F., Lopez-Tamayo, A., Merediz-Alonso, G., Olesen, D. H., Jakobsen, J., Wang, S., Garcia, M., & Bauer-Gottwein, P. (2018a). Unmanned aerial vehicle observations of water surface elevation and bathymetry in the cenotes and lagoons of the Yucatan Peninsula, Mexico. *Hydrogeology Journal*, *26*(7), 2213–2228.

Bandini, F., Olesen, D., Jakobsen, J., Kittel, C. M. M., Wang, S., Garcia, M., & Bauer-Gottwein, P. (2018b). Bathymetry observations of inland water bodies using a tethered single-beam sonar controlled by an unmanned aerial vehicle. *Hydrology and Earth System Sciences*, *22*(8), 4165–4181.

Bandini, F., Sunding, T. P., Linde, J., Smith, O., Jensen, I. K., Köppl, C. J., Butts, M., & Bauer-Gottwein, P. (2020). Unmanned Aerial System (UAS) observations of water surface elevation in a small stream: Comparison of radar altimetry, LIDAR and photogrammetry techniques. *Remote Sensing of Environment*, *237*, 111487.

Bangira, T., Alfieri, S. M., Menenti, M., & Van Niekerk, A. (2019). Comparing thresholding with machine learning classifiers for mapping complex water. *Remote Sensing*, *11*(11), 1351.

Bangira, T., Maathuis, B. H., Dube, T., & Gara, T. W. (2015). Investigating flash floods potential areas using ASCAT and TRMM satellites in the Western Cape Province, South Africa. *Geocarto International*, *30*(7), 737–754.

Barros, A. P., dos Santos, E. J., da Silva Pedro, F. K., Lemes, D. A. M., Picolo, J., Sales, G. R., Corso, V., & Bezerra, C. S. (2025). Fusion of Satellite and Drone Images for Identifying Water Bodies. *Revista de Informática Teórica e Aplicada*, *32*(1), 121–127.

Bauer-Gottwein, P., Olesen, D., Nielsen, K., Rietz, A., Frías, M. C., Dobrovolskiy, A., Kadek, A., Orlic, N., Grubesa, T., & Hiller, T. (2024). *UAS Hydrometry–Contactless airborne measurements of water level, depth, flow velocity and discharge in rivers and streams*. A European vision for hydrological observations and experimentation, Naples, Italy, 12–15 Jun 2023, GC8-Hydro-52.

Ben Moshe, L., & Lensky, N. G. (2024). Geomorphological response of alluvial streams to flood events during base-level lowering: insights from drone-based photogrammetric surveys in Dead Sea tributaries. *Remote Sensing*, *16*(8), 1346.

Biggs, J., Von Fumetti, S., & Kelly-Quinn, M. (2017). The importance of small waterbodies for biodiversity and ecosystem services: implications for policy makers. *Hydrobiologia*, *793*(1), 3–39.

Billson, J., Islam, M. S., Sun, X., & Cheng, I. (2023). Water body extraction from sentinel-2 imagery with deep convolutional networks and pixelwise category transplantation. *Remote Sensing*, *15*(5), 1253.

Binh, P. D., & Son, T. S. (2021). Monitoring spatial-temporal dynamics of small lakes based on SAR Sentinel-1 observations: a case study over Nui Coc Lake (Vietnam). *Vietnam Journal of Earth Sciences*, *44*(1), 1–17.

Blöschl, G., Bierkens, M. F., Chambel, A., Cudennec, C., Destouni, G., Fiori, A., Kirchner, J. W., McDonnell, J. J., Savenije, H. H., & Sivapalan, M. (2019). Twenty-three unsolved problems in hydrology (UPH)–a community perspective. *Hydrological Sciences Journal*, *64*(10), 1141–1158.

Breiman, L. (2001). Random forests. *Machine learning*, *45*, 5–32.

Briggs, J. (2018). The millennium development goals. In *Handbook of African Development* (pp. 300–312). Routledge.

Cameron, A. C., & Windmeijer, F. A. (1997). An R-squared measure of goodness of fit for some common nonlinear regression models. *Journal of econometrics*, *77*(2), 329–342.

Canton, H. (2021). Food and agriculture organization of the United Nations—FAO. In *The Europa directory of international organizations 2021* (pp. 297–305). Routledge.

Cao, H., Gu, X., Sun, Y., Gao, H., Tao, Z., & Shi, S. (2021). Comparing, validating and improving the performance of reflectance obtention method for UAV-Remote sensing. *International Journal of Applied Earth Observation and Geoinformation*, *102*, 102391.

Carballido, E. (2023). *Analysis of Small Lake Water Level Fluctuations by Remote Sensing in Twin Lake, Michigan*. Western Michigan University.

Casas-Mulet, R., Pander, J., Ryu, D., Stewardson, M. J., & Geist, J. (2020). Unmanned aerial vehicle (UAV)-based thermal infra-red (TIR) and optical imagery reveals multi-spatial scale controls of cold-water areas over a groundwater-dominated riverscape. *Frontiers in Environmental Science*, *8*, 64.

Chen, P., Jamet, C., Zhang, Z., He, Y., Mao, Z., Pan, D., Wang, T., Liu, D., & Yuan, D. (2021). Vertical distribution of subsurface phytoplankton layer in South China Sea using airborne lidar. *Remote sensing of environment*, *263*, 112567.

Chen, S., Johnson, F., Drummond, C., & Glamore, W. (2020). A new method to improve the accuracy of remotely sensed data for wetland water balance estimates. *Journal of Hydrology: Regional Studies*, *29*, 100689.

Chicco, D., Warrens, M. J., & Jurman, G. (2021). The coefficient of determination R-squared is more informative than SMAPE, MAE, MAPE, MSE and RMSE in regression analysis evaluation. *Peerj computer science*, *7*, e623.

Cho, M. S., & Qi, J. (2025). Remote sensing-based assessment of dam impacts on hydrology, geomorphology, ecosystems, and society–a review. *Environmental Earth Sciences*, *84*(12), 344.

Cillero Castro, C., Domínguez Gómez, J. A., Delgado Martín, J., Hinojo Sánchez, B. A., Cereijo Arango, J. L., Cheda Tuya, F. A., & Díaz-Varela, R. (2020). An UAV and satellite multispectral data approach to monitor water quality in small reservoirs. *Remote Sensing*, *12*(9), 1514.

Coppo Frias, M., Vesterhauge, A. R., Olesen, D. H., Bandini, F., Grosen, H., Nielsen, S. Y., & Bauer-Gottwein, P. (2025). Combining UAS LiDAR, Sonar, and Radar Altimetry for River Hydraulic Characterization. *Drones*, *9*(1), 31.

Cracknell, A. P. (2017). UAVs: regulations and law enforcement. *International journal of remote sensing*, *38*(8-10), 3054–3067.

Cucho-Padin, G., Loayza, H., Palacios, S., Balcazar, M., Carbajal, M., & Quiroz, R. (2020). Development of low-cost remote sensing tools and methods for supporting smallholder agriculture. *Applied Geomatics*, *12*(3), 247–263.

Dietrich, J. T. (2017). Bathymetric structure-from-motion: Extracting shallow stream bathymetry from multi-view stereo photogrammetry. *Earth Surface Processes and Landforms*, *42*(2), 355–364.

Duan, J. G., Engel, F. L., & Cadogan, A. (2023). Discharge estimation using video recordings from small unoccupied aircraft systems. *Journal of Hydraulic Engineering*, *149*(11), 04023048.

Duan, P., Wang, M., Lei, Y., & Li, J. (2021). Research on estimating water storage of small lake based on unmanned aerial vehicle 3D model. *Water resources*, *48*(5), 690–700.

Dwivedi, D., Poeppl, R. E., & Wohl, E. (2025). Hydrological connectivity: a review and emerging strategies for integrating measurement, modeling, and management. *Frontiers in Water*, *7*, 1496199.

Emanuele, P., Nives, G., Andrea, C., Carlo, C., Paolo, D., & Andrea Maria, L. (2020). Bathymetric detection of fluvial environments through UASs and machine learning systems. *Remote Sensing*, *12*(24), 4148.

Erena, M., Atenza, J. F., García-Galiano, S., Domínguez, J. A., & Bernabé, J. M. (2019). Use of drones for the topo-bathymetric monitoring of the reservoirs of the Segura River Basin. *Water*, *11*(3), 445.

Finley, J. W., & Seiber, J. N. (2014). The nexus of food, energy, and water. *Journal of agricultural and food chemistry*, *62*(27), 6255–6262.

Flener, C., Vaaja, M., Jaakkola, A., Krooks, A., Kaartinen, H., Kukko, A., Kasvi, E., Hyyppä, H., Hyyppä, J., & Alho, P. (2013). Seamless mapping of river channels at high resolution using mobile LiDAR and UAV-photography. *Remote Sensing*, *5*(12), 6382–6407.

Francis, R., Kingsford, R., & Brandis, K. (2022). Using drones and citizen science counts to track colonial waterbird breeding, an indicator for ecosystem health on the Chobe River, Botswana. *Global Ecology and Conservation*, *38*, e02231.

Gafurov, A., Usmanov, B., & Khomyakov, P. (2024). Modelling of Kuibyshev reservoir shallow water depths by bathymetric surveys and multispectral UAV imagery data: A case study. BIO Web of Conferences, 126, 01047

Gafurov, A. M., Yermolayev, O. P., Usmanov, B. M., & Khomyakov, P. V. (2021). Creation of high-precision digital elevation models using the GNSS UAV. Proceedings of the International conference "InterCarto. InterGIS", 21, 328.

Gao, A., Wu, S., Wang, F., Wu, X., Xu, P., Yu, L., & Zhu, S. (2019). A newly developed unmanned aerial vehicle (UAV) imagery based technology for field measurement of water level. *Water*, *11*(1), 124.

Gao, W., Xu, F., & Zhou, Z.-H. (2022). Towards convergence rate analysis of random forests for classification. *Artificial Intelligence*, *313*, 103788.

García-López, S., Vélez-Nicolás, M., Martínez-López, J., Sánchez-Bellón, A., Pacheco-Orellana, M. J., Ruiz-Ortiz, V., Muñoz-Pérez, J. J., & Barbero, L. (2022). Using UAV photogrammetry and automated sensors to assess aquifer recharge from a coastal wetland. *Remote Sensing*, *14*(24), 6185.

García-López, S., Vélez-Nicolás, M., Zarandona-Palacio, P., Curcio, A. C., Ruiz-Ortiz, V., & Barbero, L. (2023). UAV-borne LiDAR revolutionizing groundwater level mapping. *Science of The Total Environment*, *859*, 160272.

Gentile, V., Mróz, M., Spitoni, M., Lejot, J., Piégay, H., & Demarchi, L. (2016). Bathymetric mapping of shallow rivers with UAV hyperspectral data. Fifth International Conference on Telecommunications and Remote Sensing, 1, 43-49.

Gholizadeh, M. H., Melesse, A. M., & Reddi, L. (2016). A comprehensive review on water quality parameters estimation using remote sensing techniques. *Sensors*, *16*(8), 1298.

Giulietti, N., Allevi, G., Castellini, P., Garinei, A., & Martarelli, M. (2022). Rivers' water level assessment using UAV photogrammetry and RANSAC method and the analysis of sensitivity to uncertainty sources. *Sensors*, *22*(14), 5319.

Gu, P., Liao, A., Liu, H., Wu, W., Wu, Y., Liu, G., Cao, J., Wang, G., Jiang, X., & Hu, P. (2023). River cross-section measurement using unreviewed aerial vehicle with an improved bathymetry instrument. *Journal of Hydrology*, *624*, 129737.

Guan, T., Chang, S., Deng, Y., Xue, F., Wang, C., & Jia, X. (2025). Oriented SAR Ship Detection Based on Edge Deformable Convolution and Point Set Representation. *Remote Sensing*, *17*(9), 1612.

Guo, H., Yang, H., Qiao, B., Wang, M., & Zhu, L. (2021). Multi-resolution satellite images bathymetry inversion of Bangda Co in the western Tibetan Plateau. *International journal of remote sensing*, *42*(21), 8077–8098.

Gutsa, T., Trois, C., de Vries, R., & Mani, T. (2024). Wasted shores: Using drones to monitor the spatio-temporal evolution of debris accumulation hotspots on South Africa's Umgeni River. *Science of the Total Environment*, *955*, 176791.

Hameed, F., Qureshi, M. A., & Khalil, R. M. Z. (2022). Establishing level-area-volume relationships of Darawat reservoir using time series remote-sensing images, 15(11) 28.

Hardy, A., Makame, M., Cross, D., Majambere, S., & Msellem, M. (2017). Using low-cost drones to map malaria vector habitats. *Parasites & vectors*, *10*(1), 29.

He, J., Lin, J., & Liao, X. (2022). Fully-covered bathymetry of clear tufa lakes using UAV-acquired overlapping images and neural networks. *Journal of Hydrology*, *615*, 128666.

He, J., Lin, J., Ma, M., & Liao, X. (2021). Mapping topo-bathymetry of transparent tufa lakes using UAV-based photogrammetry and RGB imagery. *Geomorphology*, *389*, 107832.

He, J., Lin, J., Zhang, X., & Liao, X. (2023). Accurate estimation of surface water volume in tufa lake group using UAV-captured imagery and ANNs. *Measurement*, *220*, 113391.

He, J., Zhang, S., Feng, W., & Lin, J. (2024). Quantifying earthquake-induced bathymetric changes in a tufa lake using high-resolution remote sensing data. *International Journal of Applied Earth Observation and Geoinformation*, *127*, 103680.

Hirji, R. F., & Duda, A. (2025). Integrated management of lakes, reservoirs, and their basins is critical for a climate-resilient planet: an urgent wake-up call from collective amnesia. *Water Policy*, *27*(1), 66–87.

Ho, L. T., & Goethals, P. (2019). Opportunities and challenges for the sustainability of lakes and reservoirs in relation to the Sustainable Development Goals (SDGs). Water 11 (7): 1462. In.

Horsley, T., Dingwall, O., & Sampson, M. (2011). Checking reference lists to find additional studies for systematic reviews. *Cochrane database of systematic reviews* (8).

Hout, R., Maleval, V., Mahe, G., Rouvellac, E., Crouzevialle, R., & Cerbelaud, F. (2020). UAV and LiDAR data in the service of bank gully erosion measurement in Rambla de Algeciras lakeshore. *Water*, *12*(10), 2748.

Hu, X., Zhou, Z., Bahmanpouri, F., Tuo, Y., Tarpanelli, A., Barbetta, S., David, G., Wennerberg, D., Broich, K., & Merk, F. (2025). Contactless river discharge from

Unoccupied Aerial Systems hydrometry: performance evaluation using a large and diverse set of river cross sections. *Authorea Preprints*.

Hughes, T. P., Kerry, J. T., Baird, A. H., Connolly, S. R., Dietzel, A., Eakin, C. M., Heron, S. F., Hoey, A. S., Hoogenboom, M. O., & Liu, G. (2018). Global warming transforms coral reef assemblages. *Nature*, *556*(7702), 492–496.

Ichikawa, K., Ebinuma, T., Konda, M., & Yufu, K. (2019). Low-cost GNSS-R altimetry on a UAV for water-level measurements at arbitrary times and locations. *Sensors*, *19*(5), 998.

Iqbal, A., Mondal, M. S., Veerbeek, W., Khan, M. S. A., & Hakvoort, H. (2023). Effectiveness of UAV-based DTM and satellite-based DEMs for local-level flood modeling in Jamuna floodplain. *Journal of Flood Risk Management*, *16*(4), e12937.

Iverson, L. R., Prasad, A. M., Matthews, S. N., & Peters, M. (2008). Estimating potential habitat for 134 eastern US tree species under six climate scenarios. *Forest ecology and management*, *254*(3), 390–406.

Jiang, L., Bandini, F., Smith, O., Klint Jensen, I., & Bauer-Gottwein, P. (2020). The value of distributed high-resolution UAV-borne observations of water surface elevation for river management and hydrodynamic modeling. *Remote Sensing*, *12*(7), 1171.

Jiang, L., Zhou, C., & Li, X. (2023). Sub-pixel surface water mapping for heterogeneous areas from Sentinel-2 images: A case study in the Jinshui Basin, China. *Water*, *15*(8), 1446.

Jiang, W., Li, W., Zhou, J., Wang, P., & Xiao, H. (2022). Drone-based investigation of natural restoration of vegetation in the water level fluctuation zone of cascade reservoirs in Jinsha River. *Scientific Reports*, *12*(1), 12895.

Jojozi, F. N., Mbhele, T. P., & Eresia-Eke, C. (2025). Water management optimization challenges: a supply-side perspective. *Sustainable Water Resources Management*, *11*(5), 103.

Kageyama, Y., Takahashi, J., Nishida, M., Kobori, B., & Nagamoto, D. (2016). Analysis of water quality in Miharu dam reservoir, Japan, using UAV data. *IEEJ Transactions on Electrical and Electronic Engineering*, *11*, S183–S185.

Kahinda, J., Kapangaziwiri, E., Hughes, D., & Khakhu, K. (2022). A review of and scoping for water scarcity/security research in South Africa: towards a research strategy. *WRC and Institute for Water Research, Rhodes University, Pretoria/Makanda*.

Kasvi, E., Salmela, J., Lotsari, E., Kumpula, T., & Lane, S. (2019). Comparison of remote sensing based approaches for mapping bathymetry of shallow, clear water rivers. *Geomorphology*, *333*, 180–197.

Kaya, Y., Sanli, F. B., & Abdikan, S. (2023). Determination of long-term volume change in lakes by integration of UAV and satellite data: the case of Lake Burdur in Türkiye. *Environmental Science and Pollution Research*, *30*(55), 117729–117747.

Kim, J. S., Baek, D., Seo, I. W., & Shin, J. (2019). Retrieving shallow stream bathymetry from UAV-assisted RGB imagery using a geospatial regression method. *Geomorphology*, *341*, 102–114.

Kinzel, P. J., & Legleiter, C. J. (2019). sUAS-based remote sensing of river discharge using thermal particle image velocimetry and bathymetric lidar. *Remote Sensing*, *11*(19), 2317.

Kinzel, P. J., Legleiter, C. J., & Gazoorian, C. L. (2024). Reach-Scale Mapping of Surface Flow Velocities from Thermal Images Acquired by an Uncrewed Aircraft System along the Sacramento River, California, USA. *Water*, *16*(13), 1870.

Kujawa, P., Wajs, J., & Pleśniak, K. (2025). The approach to UAV image acquisition and processing for very shallow water mapping. *International Journal of Applied Earth Observation and Geoinformation*, *141*, 104604.

Kvile, K. Ø., Gundersen, H., Poulsen, R. N., Sample, J. E., Salberg, A.-B., Ghareeb, M. E., Buls, T., Bekkby, T., & Hancke, K. (2024). Drone and ground-truth data collection, image annotation and machine learning: A protocol for coastal habitat mapping and classification. *MethodsX*, *13*, 102935.

Kwon, S., Gwon, Y., Kim, D., Seo, I. W., & You, H. (2023). Unsupervised classification of riverbed types for bathymetry mapping in shallow rivers using UAV-based hyperspectral imagery. *Remote Sensing*, *15*(11), 2803.

La Salandra, M., Colacicco, R., Dellino, P., & Capolongo, D. (2023). An effective approach for automatic river features extraction using high-resolution UAV imagery. *Drones*, *7*(2), 70.

La Salandra, M., Colacicco, R., Panza, S., Fumai, G., Dellino, P., & Capolongo, D. (2025). RivAIr: A custom-designed UAV-based sensor for real-time water area segmentation and surface velocity estimation. *International Journal of Applied Earth Observation and Geoinformation*, *142*, 104720.

Lahmeri, M.-A., Fakharizadeh, P., Mustieles-Pérez, V., Vossiek, M., Krieger, G., & Schober, R. (2025). Sensing Accuracy Optimization for Multi-UAV SAR Interferometry with Data Offloading. *arXiv preprint arXiv:2507.11284*.

Lally, H., O'Connor, I., Jensen, O., & Graham, C. (2019). Can drones be used to conduct water sampling in aquatic environments? A review. *Science of the Total Environment*, *670*, 569–575.

Langhammer, J., Bernsteinová, J., & Miřijovský, J. (2017). Building a high-precision 2D hydrodynamic flood model using UAV photogrammetry and sensor network monitoring. *Water*, *9*(11), 861.

Lawford, R., Strauch, A., Toll, D., Fekete, B., & Cripe, D. (2013). Earth observations for global water security. *Current Opinion in Environmental Sustainability*, *5*(6), 633–643.

Lee, C.-H., Liu, L.-W., Wang, Y.-M., Leu, J.-M., & Chen, C.-L. (2022). Drone-based bathymetry modeling for mountainous shallow rivers in Taiwan using machine learning. *Remote Sensing*, *14*(14), 3343.

Lee, G., Choi, M., Yu, W., & Jung, K. (2019). Creation of river terrain data using region growing method based on point cloud data from UAV photography. *Quaternary International*, *519*, 255–262.

Legleiter, C., & Harrison, L. (2018). Remotely sensed data and field measurements used for bathymetric mapping of the upper Sacramento River in northern California. *US Geological Survey data release, 10, 5066*.

Legleiter, C. J., & Harrison, L. R. (2019). Remote sensing of river bathymetry: Evaluating a range of sensors, platforms, and algorithms on the upper Sacramento River, California, USA. *Water Resources Research*, *55*(3), 2142–2169.

Legleiter, C. J., & Harrison, L. R. (2024). Evaluating the potential for efficient, UAS-based reach-scale mapping of river channel bathymetry from multispectral images. *Frontiers in Remote Sensing*, *5*, 1305991.

Lejot, J., Delacourt, C., Piégay, H., Fournier, T., Trémélo, M. L., & Allemand, P. (2007). Very high spatial resolution imagery for channel bathymetry and topography from an unmanned mapping controlled platform. *Earth Surface Processes and*

*Landforms: The Journal of the British Geomorphological Research Group*, *32*(11), 1705–1725.

Li, C., Yue, C., Li, H., & Wang, Z. (2024). Context-aware SAR image ship detection and recognition network. *Frontiers in Neurorobotics*, *18*, 1293992.

Li, M., Zhao, C., Huang, Q., Pan, T., Yesou, H., Nerry, F., & Li, Z.-L. (2025). Combining Landsat 5 TM and UAV images to estimate river discharge with limited ground-based flow velocity and water level observations. *Remote Sensing of Environment*, *318*, 114610.

Li, Y., Yang, W., Li, J., Zhang, Z., & Meng, L. (2022). A novel method for mapping lake bottom topography using the GSW dataset and measured water level. *Remote Sensing*, *14*(6), 1423.

Liaw, A., & Wiener, M. (2002). Classification and regression by randomForest. *R news*, *2*(3), 18–22.

Liu, J., Jiang, L., Bandini, F., Kittel, C. M., Balbarini, N., Hansted, N. G., Grosen, H., & Bauer-Gottwein, P. (2022). Spatio-temporally varying Strickler coefficient: A calibration approach applied to a Danish river using in-situ water surface elevation and UAS altimetry. *Journal of Hydrology*, *613*, 128443.

Liu, Y., Wang, Z., Kou, X., Cao, Y., & Yue, H. (2025). Lake depth inversion based on UAV and Sentinel-2 data. *Earth Science Informatics*, *18*(1), 1–18.

Mancini, D., Antoniazza, G., Roncoroni, M., Mettra, F., & Lane, S. N. (2024). Heuristic estimation of river bathymetry in braided streams using digital image processing. *Earth Surface Processes and Landforms*, *49*(12), 3889–3912.

Mandlburger, G., Hauer, C., Wieser, M., & Pfeifer, N. (2015). Topo-bathymetric LiDAR for monitoring river morphodynamics and instream habitats—A case study at the Pielach River. *Remote Sensing*, *7*(5), 6160–6195.

Mandlburger, G., Kölle, M., Nübel, H., & Soergel, U. (2021). BathyNet: A deep neural network for water depth mapping from multispectral aerial images. *PFG–Journal of Photogrammetry, Remote Sensing and Geoinformation Science*, *89*(2), 71–89.

Mandlburger, G., Pfennigbauer, M., Schwarz, R., Flöry, S., & Nussbaumer, L. (2020). Concept and performance evaluation of a novel UAV-borne topo-bathymetric LiDAR sensor. *Remote Sensing*, *12*(6), 986.

Mandlburger, G., Pfennigbauer, M., & Wieser, M. (2016). Lidar bathymetry from UAVs. *Coordinates*, *12*(12), 12–16.

Mandlburger, G., Weiß, R., & Artz, T. (2020). Mapping of water surface levels and slopes with single photon lidar–a case study at the river Rhine. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, *43*, 57–64.

Masoudimoghaddam, M., Yazdi, J., & Shahsavandi, M. (2025). A low-cost ultrasonic sensor for online monitoring of water levels in rivers and channels. *Flow Measurement and Instrumentation*, *102*, 102777.

Massuel, S., Feurer, D., El Maaoui, M. A., & Calvez, R. (2022). Deriving bathymetries from unmanned aerial vehicles: a case study of a small intermittent reservoir. *Hydrological Sciences Journal*, *67*(1), 82–93.

Matsimbe, J., Mdolo, W., Kapachika, C., Musonda, I., & Dinka, M. (2022). Comparative utilization of drone technology vs. traditional methods in open pit stockpile volumetric computation: A case of njuli quarry, Malawi. *Frontiers in built environment*, *8*, 1037487.

McFeeters, S. K. (1996). The use of the Normalized Difference Water Index (NDWI) in the delineation of open water features. *International journal of remote sensing*, *17*(7), 1425–1432.

Medvedev, A., Telnova, N., Alekseenko, N., Koshkarev, A., Kuznetchenko, P., Asmaryan, S., & Narykov, A. (2020). UAV-derived data application for environmental monitoring of the coastal area of Lake Sevan, Armenia with a changing water level. *Remote Sensing*, *12*(22), 3821.

Messager, M. L., Lehner, B., Grill, G., Nedeva, I., & Schmitt, O. (2016). Estimating the volume and age of water stored in global lakes using a geo-statistical approach. *Nature communications*, *7*(1), 13603.

Miřijovský, J., & Šulc-Michalková, M. (2014). Spatial-Temporal Evolution of the Unique Preserved Meandering System in Central Europe. In *Modern Trends in Cartography: Selected Papers of CARTOCON 2014* (pp. 507–517). Springer.

Mishra, V., Avtar, R., Prathiba, A., Mishra, P. K., Tiwari, A., Sharma, S. K., Singh, C. H., Chandra Yadav, B., & Jain, K. (2023). Uncrewed aerial systems in water resource management and monitoring: a review of sensors, applications, software, and issues. *Advances in Civil Engineering*, *2023*(1), 3544724.

Mohamad, N., Abdul Khanan, M. F., Ahmad, A., Md Din, A. H., & Shahabi, H. (2019). Evaluating water level changes at different tidal phases using UAV photogrammetry and GNSS vertical data. *Sensors*, *19*(17), 3778.

Mokoena, Q., Daniyan, I., Mpofu, K., & Abisuga, O. (2022). Towards strategic management of drone application process and regulation in South Africa. *South African Journal of Industrial Engineering*, *33*(4), 177–196.

Mourato, S., Fernandez, P., Pereira, L., & Moreira, M. (2017). Improving a DSM obtained by unmanned aerial vehicles for flood modelling. IOP Conference Series: Earth and Environmental Science, 95 (2), 022014.

Mudiyanselage, S., Abd-Elrahman, A., Wilkinson, B., & Lecours, V. (2022). Satellite-derived bathymetry using machine learning and optimal Sentinel-2 imagery in South-West Florida coastal waters. *GIScience & Remote Sensing*, *59*(1), 1143–1158.

Mutanga, O., Adam, E., & Cho, M. A. (2012). High density biomass estimation for wetland vegetation using WorldView-2 imagery and random forest regression algorithm. *International Journal of Applied Earth Observation and Geoinformation*, *18*, 399–406.

Najar, M. A., Benshila, R., Bennioui, Y. E., Thoumyre, G., Almar, R., Bergsma, E. W., Delvit, J.-M., & Wilson, D. G. (2022). Coastal bathymetry estimation from Sentinel-2 satellite imagery: Comparing deep learning and physics-based approaches. *Remote Sensing*, *14*(5), 1196.

Ngo, P. L., Pham, V. H., Bui, N. L., Phan, H. A. T., Vo, H. B., Velavan, T. P., & Tran, D. K. (2025). Detection of small water bodies for vector control using deep learning on multispectral imagery from unmanned aerial vehicles. *Discover Artificial Intelligence*, *5*(1), 170.

Özcan, O., & Özcan, O. (2021). Multi-temporal UAV based repeat monitoring of rivers sensitive to flood. *Journal of Maps*, *17*(3), 163–170.

Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., Shamseer, L., Tetzlaff, J. M., Akl, E. A., & Brennan, S. E. (2021). The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. *bmj*, *372*.

Pai, H., Malenda, H., Briggs, M. A., Singha, K., González-Pinzón, R., Gooseff, M., Tyler, S., & Team, A. (2017). Potential for small unmanned aircraft systems applications for identifying groundwater-surface water exchange in a meandering river reach. *Geophysical Research Letters*, *44*(23), 11,868–811,877.

Pal, M. (2005). Random forest classifier for remote sensing classification. *International journal of remote sensing*, *26*(1), 217–222.

Pingel, T. J., Saavedra, A., & Cobo, L. (2021). Deriving land and water surface elevations in the northeastern Yucatán Peninsula using PPK GPS and UAV-based structure from motion. *Papers in Applied Geography*, *7*(3), 294–315.

Pizarro, A., Valera-Gran, D., Navarrete-Muñoz, E.-M., & Dal Sasso, S. F. (2024). The Use of Unmanned Aerial Systems for River Monitoring: A Bibliometric Analysis Covering the Last 25 Years. *Hydrology*, *11*(6), 80.

Pricope, N. G., Halls, J. N., Mapes, K. L., Baxley, J. B., & Wu, J. J. (2020). Quantitative comparison of UAS-borne LiDAR systems for high-resolution forested wetland mapping. *Sensors*, *20*(16), 4453.

Purnell, D. J., Gomez, N., Minarik, W., Porter, D., & Langston, G. (2021). Precise water level measurements using low-cost GNSS antenna arrays. *Earth Surface Dynamics Discussions*, *2021*, 1–19.

Quesada-Román, A., Ballesteros-Cánovas, J. A., Granados-Bolaños, S., Birkel, C., & Stoffel, M. (2020). Dendrogeomorphic reconstruction of floods in a dynamic tropical river. *Geomorphology*, *359*, 107133.

Ramillien, G., Frappart, F., & Seoane, L. (2014). Application of the regional water mass variations from GRACE satellite gravimetry to large-scale water management in Africa. *Remote Sensing*, *6*(8), 7379–7405.

Rehamnia, I., & Mahdavi-Meymand, A. (2025). Advancing reservoir water level predictions: Evaluating conventional, ensemble and integrated swarm machine learning approaches. *Water Resources Management*, *39*(2), 779–794.

Ridolfi, E., Alfonso, L., Di Baldassarre, G., Dottori, F., Russo, F., & Napolitano, F. (2014). An entropy approach for the optimization of cross-section spacing for river modelling. *Hydrological Sciences Journal*, *59*(1), 126–137.

Ridolfi, E., & Manciola, P. (2018). Water level measurements from drones: A pilot case study at a dam site. *Water*, *10*(3), 297.

Ritchie, A. C., Warrick, J. A., East, A. E., Magirl, C. S., Stevens, A. W., Bountry, J. A., Randle, T. J., Curran, C. A., Hilldale, R. C., & Duda, J. J. (2018). Morphodynamic evolution following sediment release from the world's largest dam removal. *Scientific Reports*, *8*(1), 13279.

Rossi, L., Mammi, I., & Pelliccia, F. (2020). UAV-derived multispectral bathymetry. *Remote Sensing*, *12*(23), 3897.

Saeidi, V., Seydi, S. T., Kalantar, B., Ueda, N., Tajfirooz, B., & Shabani, F. (2023). Water depth estimation from Sentinel-2 imagery using advanced machine learning methods and explainable artificial intelligence. *Geomatics, Natural Hazards and Risk*, *14*(1), 2225691.

Schumann, G. J.-P., Muhlhausen, J., & Andreadis, K. M. (2019). Rapid mapping of small-scale river-floodplain environments using UAV SfM supports classical theory. *Remote Sensing*, *11*(8), 982.

Schwarz, R., Mandlburger, G., Pfennigbauer, M., & Pfeifer, N. (2019). Design and evaluation of a full-wave surface and bottom-detection algorithm for LiDAR bathymetry of very shallow waters. *ISPRS journal of photogrammetry and remote sensing*, *150*, 1–10.

Shangguan, S. (2023). Reliable Detection of Water Areas in Multispectral Drone Imagery: A faster region-based CNN model for accurately identifying the location of small-scale standing water bodies. In: KTH Royal Institute of Technology. TRITA-EECS-EX, 2, 1749935.

Shen, Q. (2022). Estimation of Water Depth from Multispectral Drone Imagery: A suitability assessment of CNN models for bathymetry retrieval in shallow water areas. In. TRITA-EECS-EX, 2, 1750629.

Sibanda, M., Mutanga, O., Chimonyo, V. G., Clulow, A. D., Shoko, C., Mazvimavi, D., Dube, T., & Mabhaudhi, T. (2021). Application of drone technologies in surface water resources monitoring and assessment: A systematic review of progress, challenges, and opportunities in the global south. *Drones*, *5*(3), 84.

Singh, K. (2023). Current trends in River Bathymetry using UAV-borne technology to inform E-flow assessments in Southern Africa. Colombo, Sri Lanka: International Water Management Institute (IWMI). CGIAR Initiative on Digital Innovation. 17p.

Slocum, R. K., Parrish, C. E., & Simpson, C. H. (2020). Combined geometric-radiometric and neural network approach to shallow bathymetric mapping with UAS imagery. *ISPRS Journal of Photogrammetry and Remote Sensing*, *169*, 351–363.

Stephens, E. C., Martin, G., Van Wijk, M., Timsina, J., & Snow, V. (2020). Impacts of COVID-19 on agricultural and food systems worldwide and on progress to the sustainable development goals. In (Vol. 183, pp. 102873): Elsevier.

Szostak, B., Specht, M., Burdziakowski, P., Stateczny, A., Specht, C., & Lewicka, O. (2023). Methodology for performing bathymetric measurements of shallow waterbodies using an UAV, and their processing based on the SVR algorithm. *Measurement*, *223*, 113720.

Szostak, R., Pietroń, M., Wachniew, P., Zimnoch, M., & Ćwiąkała, P. (2023). Estimation of River Water Surface Elevation Using UAV Photogrammetry and Machine Learning. *arXiv preprint arXiv:2306.06118*.

Szostak, R., Pietroń, M., Wachniew, P., Zimnoch, M., & Ćwiąkała, P. (2024). Estimation of Small-Stream Water Surface Elevation Using UAV Photogrammetry and Deep Learning. *Remote Sensing*, *16*(8), 1458.

Templin, T., Popielarczyk, D., & Kosecki, R. (2018). Application of low-cost fixed-wing UAV for inland lakes shoreline investigation. *Pure and Applied Geophysics*, *175*(9), 3263–3283.

Tymków, P., Jóźków, G., Walicka, A., Karpina, M., & Borkowski, A. (2019). Identification of water body extent based on remote sensing data collected with unmanned aerial vehicle. *Water*, *11*(2), 338.

Van Eck, N., & Waltman, L. (2010). Software survey: VOSviewer, a computer program for bibliometric mapping. *scientometrics*, *84*(2), 523–538.

Vélez-Nicolás, M., García-López, S., Barbero, L., Ruiz-Ortiz, V., & Sánchez-Bellón, Á. (2021). Applications of unmanned aerial systems (UASs) in hydrology: A review. *Remote Sensing*, *13*(7), 1359.

Wang, J., Chen, M., Zhu, W., Hu, L., & Wang, Y. (2022). A combined approach for retrieving bathymetry from aerial stereo rgb imagery. *Remote Sensing*, *14*(3), 760.

Wang, X., Yang, Y., Darko, A., Chan, A. P., & Chi, H.-L. (2024). The impact of penalties, incentives, and monitoring costs on the stakeholders' decision-making behaviors in non-compliance drone operations. *Technology in Society*, *77*, 102589.

Wang, Y., Yan, N., Zhu, W., Ma, Z., & Wu, B. (2025). A method to estimate the water storage of on-farm reservoirs by detecting slope gradients based on multi-spectral drone data. *Agricultural Water Management*, *307*, 109241.

Wheeler, P., Organ, A., & Esselman, J. (2025). *Implementation of Uncrewed Aircraft Systems Operational Capabilities: A Guide* (0309992877).

Wienhold, K. J., Li, D., Li, W., & Fang, Z. N. (2023). Flood inundation and depth mapping using unmanned aerial vehicles combined with high-resolution multispectral imagery. *Hydrology*, *10*(8), 158.

Witek, M., Walusiak, G., Halicki, M., Remisz, J., Borowicz, D., Parzóch, K., Kasprzak, Ł., Langhammer, J., Gallay, M., & Miřijovský, J. (2025). Reconstructing bed topography of a shallow river from close-range aerial imagery: Multi-UAV experimental campaign in the Izera river (SW Poland/N Czechia). *Geomorphology*, *471*, 109544.

Woodget, A., Carbonneau, P., Visser, F., & Maddock, I. P. (2015). Quantifying submerged fluvial topography using hyperspatial resolution UAS imagery and structure from motion photogrammetry. *Earth Surface Processes and Landforms*, *40*(1), 47–64.

Woodget, A. S., Austrums, R., Maddock, I. P., & Habit, E. (2017). Drones and digital photogrammetry: from classifications to continuums for monitoring river habitat and hydromorphology. *Wiley Interdisciplinary Reviews: Water*, *4*(4), e1222.

Woodget, A. S., Dietrich, J. T., & Wilson, R. T. (2019). Quantifying below-water fluvial geomorphic change: The implications of refraction correction, water surface elevations, and spatially variable error. *Remote Sensing*, *11*(20), 2415.

Woolway, R. I., Kraemer, B. M., Lenters, J. D., Merchant, C. J., O'Reilly, C. M., & Sharma, S. (2020). Global lake responses to climate change. *Nature Reviews Earth & Environment*, *1*(8), 388–403.

Xu, H. (2006). Modification of normalised difference water index (NDWI) to enhance open water features in remotely sensed imagery. *International journal of remote sensing*, *27*(14), 3025–3033.

Yang, H., Guo, H., Dai, W., Nie, B., Qiao, B., & Zhu, L. (2022). Bathymetric mapping and estimation of water storage in a shallow lake using a remote sensing inversion method based on machine learning. *International Journal of Digital Earth*, *15*(1), 789–812.

Yang, S., Wang, J., Wang, P., Gong, T., & Liu, H. (2019a). Low altitude unmanned aerial vehicles (UAVs) and satellite remote sensing are used to calculated river discharge attenuation coefficients of ungauged catchments in arid desert. *Water*, *11*(12), 2633.

Yang, S., Wang, P., Lou, H., Wang, J., Zhao, C., & Gong, T. (2019b). Estimating river discharges in ungauged catchments using the slope–area method and unmanned aerial vehicle. *Water*, *11*(11), 2361.

Yigzaw, W., Li, H. Y., Demissie, Y., Hejazi, M. I., Leung, L. R., Voisin, N., & Payn, R. (2018). A new global storage-area-depth data set for Modeling reservoirs in land surface and earth system models. *Water Resources Research*, *54*(12), 10,372–310,386.

Zaludin, Z., & Harituddin, A. S. M. (2019). Challenges and trends of changing from hover to forward flight for a converted hybrid fixed wing vtol uas from automatic flight

control system perspective. 2019 IEEE 9th International Conference on System Engineering and Technology (ICSET), 7 October 2019, Sah Alam, Malaysia.
Zhan, P., Song, C., Luo, S., Ke, L., Liu, K., & Chen, T. (2022). Investigating different timescales of terrestrial water storage changes in the northeastern Tibetan Plateau. *Journal of Hydrology*, *608*, 127608.
Zhang, C., Sun, A. r., Hassan, M. A., & Qin, C. (2022). Assessing through-water structure-from-motion photogrammetry in gravel-bed rivers under controlled conditions. *Remote Sensing*, *14*(21), 5351.
Zhao, H., Yin, X., Li, A., Zhang, H., Pan, D., Pan, J., Zhu, J., Wang, M., Sun, S., & Wang, Q. (2023). Intelligent segmentation and change detection of dams based on uav remote sensing images. *Remote Sensing*, *15*(23), 5526.
Zhou, M., Lee, A. C., Alip, A. E., Dieu, H. T., Leong, Y. L., & Ooi, S. K. (2025). Robust Bathymetric Mapping in Shallow Waters: A Digital Surface Model-Integrated Machine Learning Approach Using UAV-Based Multispectral Imagery. *Remote Sensing*, *17*(17), 3066.
Zhou, W., Tang, Y., Jing, W., Li, Y., Yang, J., Deng, Y., & Zhang, Y. (2023). A comparison of machine learning and empirical approaches for deriving bathymetry from multispectral imagery. *Remote Sensing*, *15*(2), 393.
Zhou, Z.-H. (2025a). *Ensemble methods: foundations and algorithms*. CRC press.
Zhou, Z., Riis-Klinkvort, L., Ahrnkiel Jørgensen, E., Haugård Olesen, D., Rietz Vesterhauge, A., Coppo Frías, M., Lavish, M., Nielsen, S., Gustafsson, D., & Wennerberg, D. (2025b). UAS hydrometry: contactless river water level, bathymetry, and flow velocity–the Rönne river dataset. *Scientific Data*, *12*(1), 294.
Zingaro, M., La Salandra, M., & Capolongo, D. (2022). New perspectives of earth surface remote detection for hydro-geomorphological monitoring of rivers. *Sustainability*, *14*(21), 14093.
Zinke, P., & Flener, C. (2013). Experiences from the use of unmanned aerial vehicles (UAV) for river bathymetry modelling in Norway. *Vann*, *48*(3), 351–360.