Assessing the utility of drone technology in estimating surface water temperature, total suspended solids (TSS) and Chromophoric dissolved organic matter (CDOM) in reservoirs: A case study in the uMngeni catchment.

by

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PREFACE

The research in this dissertation was completed by the candidate while based in the Discipline of Hydrology, School of Agricultural, Earth and Environmental Sciences of the College of Agriculture, Engineering and Science, University of KwaZulu-Natal, Pietermaritzburg, South Africa. The research was financially supported by The Water Research Commission of South Africa, Project No. C2022/2023-00912, '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'.

The contents of this work have not been submitted in any form to another university, except where the work of others is acknowledged in the text; the results reported are due to investigations by the candidate.

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DECLARATION 1: PLAGIARISM

I, Shannyn Jade Pillay declare that:

(i) the research reported in this dissertation, except where otherwise indicated or acknowledged, is my original work

(ii) this dissertation has not been submitted in full or in part for any degree or examination to any other university

(iii) this dissertation does not contain other persons' data, pictures, graphs or other information unless specifically acknowledged as being sourced from other persons

(iv) this dissertation does not contain other persons' writing unless expressly acknowledged as being sourced from other researchers. Where other written sources have been quoted, then:

a) their words have been re-written, but the general information attributed to them has been referenced

b) where their exact words have been used, their writing has been placed inside quotation marks and referenced

(v) where I have used material for which publications followed, I have indicated in detail my role in the work

(vi) this dissertation is primarily a collection of material prepared by me, published as journal articles or presented as a poster or oral presentations at conferences. In some cases, additional material has been included

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DECLARATION 2: PUBLICATIONS

Chapter 2

Publication 1: **Pillay, S.J**.; Bangira, T.; Sibanda, M.; Kebede Gurmessa, S.; Clulow, A.; Mabhaudhi, T. (2024) Assessing Drone-Based Remote Sensing for Monitoring Water Temperature, Suspended Solids and CDOM in Inland Waters: A Global Systematic Review of Challenges and Opportunities. Drones. 8, 733. https://doi.org/10.3390/drones8120733

Chapter two provides a comprehensive analysis of using UAV-based remote sensing for monitoring surface water temperature, total suspended solids (TSS) and Chromophoric dissolved organic matter (CDOM) in small inland water bodies. While satellite remote sensing has many limitations for monitoring small water bodies, this chapter emphasises the advantages of UAV-based remote sensing, such as their capacity to deliver high-resolution and near-real-time data. Chapter two explores various sensor technologies, machine learning algorithms and statistical methods, highlighting their advantages and disadvantages, and concludes with a call for integrating UAV, satellite and in-situ methods and for increased research to address limitations, specifically in underrepresented regions like southern Africa.

Author Contributions: Conceptualisation and design of the review, S.J.P., T.B., M.S., S.K.G., A.C. and T.M., S.J.P. performed this research and drafted the manuscript, T.B., M.S. and T.M. edited the manuscript.

Chapter 3

Publication 2 (*in press*): **Pillay, S.J**.; Bangira, T.; Sibanda, M.; Kebede Gurmessa, S.; Clulow, A.; Mabhaudhi, T. (2025) Assessing the Utility of Drone Technology in Estimating Surface Water Temperature, Total Suspended Solids and Chromophoric Dissolved Organic Matter in Reservoirs: A Case Study of the High Flight Farm Dam.

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DECLARATION 3: ARTIFICIAL INTELLEGENCE

I, Shannyn Jade Pillay declare that I made use of generative AI in this thesis in the following areas:

(i) Planning of the methodology, meta-analysis and initial thesis drafts

(ii) For language editing

In all instances, the content generated by AI was fully interrogated for applicability, accuracy of content, and plagiarism. Citations were added to statements where applicable, to assign credit to the authors. Where generative AI was used in this thesis, this is indicated in the relevant section, with full details enclosed.

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ABSTRACT

Over the past few decades, South Africa has faced severe water shortages, primarily due to the declining quality of its natural water supplies. This decline has further strained irrigation standards, directly impacting crop yields, livestock health and soil fertility. This has emphasised the need for advanced, near-real-time approaches to assess and monitor key water quality parameters affecting irrigation water quality, such as water temperature, total suspended solids (TSS), and Chromophoric dissolved organic matter (CDOM). This research explores the utility of UAV-based remote sensing for monitoring water quality parameters in small reservoirs to address the limitations of traditional remote sensing and ground-based methods, which are often labour-intensive, costly and lack sufficient spatial and temporal coverage. Chapter 1 introduces the research problem, highlighting the increasing pressure on water resources in southern Africa's resources due to climate change, population growth and land-use changes. It outlines the study's objectives, which include developing a robust methodology for using UAV-derived data to monitor key water quality parameters and improving decision-making in water resource management at the farm scale. Chapter 2 presents a global systematic review of the literature for UAV-based remote sensing for water quality monitoring. It critically evaluates advancements in sensor technology, machine learning algorithms and statistical approaches, identifying key research gaps. The chapter emphasizes the potential of UAVs to provide high-resolution, real-time data but notes challenges such as cost, regulatory constraints and the lack of standardized validation protocols. Chapter 3 provides a case study of the High Flight Farm dam in the uMngeni catchment, illustrating the application approach of UAV-derived data in monitoring water temperature, TSS, and CDOM. The study demonstrates the integration of UAV-based observations with machine learning techniques and model development to produce high-accuracy predictive spatial maps that inform sustainable agricultural practices. Finally, Chapter 4 synthesises the findings, addressing limitations such as weather and operational constraints while offering recommendations for future research. These include expanding research on underrepresented water bodies and promoting interdisciplinary collaborations to enhance the accessibility and scalability of UAV technology in water quality monitoring.

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This MSc is dedicated to the great MSC, Mark Steven Chetty. A true inspiration and role model. We miss you dearly.

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"And we know that in all things God works for the good of those who love him, who have been called according to his purpose" -Romans 8.28

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CHAPTER 1: INTRODUCTION

1.1 Background of the study

Freshwater stored in water bodies plays a vital role in agricultural productivity and food security (Hunt and Daughtry, 2018). In South Africa, irrigation accounts for up to 60% of the country's freshwater use (Von Bormann and Gulati, 2014, Bronkhorst et al., 2017). However, the growing pressures of climate change, rapid population growth, and urbanisation have increased competition for water resources, placing agriculture under significant stress. Additionally, anthropogenic activities within catchments, exacerbated by climate change, have led to the rapid degradation of water quality (Hu et al., 2021).

Over the past few decades, South Africa has faced severe water shortages, especially due to the declining quality of its natural water supplies (Edokpayi et al., 2017). This decline has imposed further strain on irrigation standards, directly impacting crop yields, livestock health, and soil fertility. Key water quality indicators, including water temperature, total suspended solids (TSS), pH, chlorophyll-a, water clarity, metals, dissolved organic matter, and total coliform concentrations, such as Escherichia coli (E. coli), are crucial for assessing the health of water resources and ecosystems (Edokpayi et al., 2017). Effective monitoring of these parameters is essential to improve livestock and crop health (El Bilali and Taleb, 2020).

South Africa's irrigation water is sourced from a variety of systems, including lakes, rivers, rainfall, groundwater, and man-made structures such as dams and reservoirs (El Bilali and Taleb, 2020). However, the quality of these sources significantly influences their suitability for irrigation. Literature sources highlight the challenges posed by poor water quality; for instance, high sediment loads in irrigation water can render it unsuitable, as demonstrated by(Bhatti et al., 2021), who noted emitter clogging as a major issue in drip irrigation systems, leading to reduced efficiency and crop water stress. Additionally, floating particles such as sand and organic matter adversely affect the longevity and performance of irrigation networks. Water temperature variations in reservoirs also pose challenges. Rajagopalan et al. (2018) observed that irrigation water sourced from the cooler downstream ends of reservoirs could adversely impact soil temperatures and crop yields, especially for temperature-sensitive crops during critical growth stages. Extreme water temperatures may stress plant roots and cause damage (Feller and Irina, 2014). Furthermore, fluctuating water temperatures promote algal growth, leading to harmful algal blooms that disrupt biological processes in reservoirs and surrounding ecosystems (Nazari-Sharabian et al., 2018). Another critical water quality parameter is Chromophoric Dissolved Organic Matter (CDOM), a key component of Dissolved Organic Matter (DOM). CDOM, derived from residential, agricultural, and industrial runoff, reduces light penetration in water, limiting the availability of essential nutrients for crop growth (Zheng et al., 2023). Additionally, CDOM can bind to certain nutrients in the water, making them less readily available for plant uptake, further impacting the nutrient balance essential for optimal plant growth (Guo and Marschner, 1995). Furthermore, understanding the temporal and spatial distribution of water temperature, TSS, and CDOM is vital for assessing water quality and its implications for agriculture, water resource management, and aquatic ecosystems (Khouni et al., 2021).

In the past, water quality monitoring of water bodies was undertaken using ground-based measurements since they are precise and provide direct, detailed observations. However, ground-based methods are labour-intensive, costly and prone to human error. Additionally, these methods are impractical for large-scale and frequent monitoring. To overcome these challenges, remote sensing technology that utilises satellite-based sensors was adopted to derive spatial and temporal data for water quality assessment of water bodies (Gitelson et al., 1993, Khouni et al., 2021). While satellites such as MODIS, Landsat, and Sentinel-2 offer valuable multispectral imagery, their applications for monitoring small water bodies are limited. This limitation arises from their coarse spatial resolution and infrequent data collection intervals, which hinder the detection of fine-scale changes in water quality (Khanal et al., 2020). As an alternative, Unmanned Aerial Vehicles (UAVs), commonly known as drones, offer a reliable, efficient, and real-time solution for water quality assessment at local scales. Sensors on board UAVs provide real-time, high spatial-resolution data, surpassing the capabilities of satellite-derived data (Nhamo et al., 2018).

The integration of UAVs into water quality monitoring holds significant potential for transforming South Africa's agricultural sector, particularly for smallholder farmers. UAVs are particularly suitable for mapping small water bodies, which often serve as critical water sources for smallholder farmers. By delivering timely and accurate information on water quality, UAVs enable farmers to make informed decisions about irrigation management, mitigate crop stress, and address challenges such as thermal and algal plumes. This technology has the potential to enhance crop productivity, improve water use efficiency, and build resilience against the impacts of climate change (Khatri-Chhetri. A, 2016).

The sustainability of agriculture in South Africa depends on the continuous monitoring of water quality to ensure the availability of irrigation water that meets the required standards. (Matthews, 2015, Adjovu, 2023). Furthermore, polluted water sources not only compromise agricultural productivity but also contribute to the spread of diseases and food insecurity. For smallholder farmers, the poor quality of farm reservoirs can result in significant losses in crop production and livestock health (Namugize et al., 2018). Thus, the urgent need for sustainable irrigation practices underscores the importance of closely monitoring and managing water quality to mitigate risks and ensure agricultural resilience.

1.2 Problem statement

Surface water stored in small reservoirs plays a critical socio-economic and ecological role, particularly in agricultural regions of South Africa. The Department of Water and Sanitation recognises these water bodies as essential for irrigation, food production, and environmental sustainability (Knight, 2019). However, deteriorating water quality which is driven by climate change, land-use changes and pollution poses a significant threat. Parameters such as Total Suspended Solids (TSS), Chromophoric Dissolved Organic Matter (CDOM) and surface water temperature are key indicators of water quality as they influence sediment transport, light availability and aquatic ecosystem health. Although monitoring these parameters is essential for understanding irrigation suitability and ecosystem functions, traditional monitoring techniques remain inadequate at the farm scale. While ground-based methods are accurate, they are also labour-intensive, costly and offer limited spatial coverage. Furthermore, while satellite-based remote sensing is beneficial for large-scale assessments, it is limited by coarse resolution and low revisit frequency, making it unsuitable for small water bodies such as farm reservoirs (Khouni et al., 2021, Khanal et al., 2020). Recent advances in Unmanned Aerial Vehicle (UAV) technology have introduced new possibilities for high-resolution, near-real-time monitoring of water quality. UAVs offer greater flexibility, precision and spatial detail, specifically when integrated with multispectral and thermal sensors. However, the application of drone-based remote sensing coupled with machine learning techniques uses for estimating TSS, CDOM and surface water temperature remains limited in the literature, especially in southern Africa. Existing literature focuses on other water quality parameters apart from TSS, CDOM and surface water temperature or focuses on the use UAVs for sample collection rather than remote sensing, highlighting a critical methodological gap therefore, this study addresses both the technical limitations of existing monitoring methods and the geographic underrepresentation in current research.

1.3 Aim

The aim of this project is to illustrate, through a case study of the High Flight Farm dam in the uMngeni catchment of KZN, how remotely sensed data acquired by sensors onboard drones can be used for water quality monitoring at a farm scale assess the utility of drone-based remote sensing in estimating surface water temperature, total suspended solids (TSS) and Chromophoric dissolved organic matter (CDOM), in the High Flight farm dam in the uMngeni catchment.

1.4 Objectives

The specific objectives to meet this aim are to:

- To critically review existing remote sensing models and methodologies used to monitor surface water temperature, Total Suspended Solids (TSS) and Chromophoric Dissolved Organic Matter (CDOM).
- To assess the inter-seasonal variability of surface water temperature, TSS and CDOM concentrations using UAV-derived multispectral and thermal data combined with machine learning algorithms.

1.5 Research questions

- How do UAV-based estimates of surface water temperature, TSS and CDOM compare in precision and accuracy to traditional remote sensing techniques, such as satellite imagery, specifically for small reservoirs?
- What are the advantages and limitations of utilising UAV-mounted sensors over satellite-based approaches in monitoring water quality parameters at the farm scale?
- To what extent can UAV-derived data coupled with machine learning algorithms, accurately capture the spatial and inter-seasonal variability of TSS, CDOM and surface water temperature?

1.6 Thesis structure

The thesis contains four chapters. Chapters 2 and 3 can be regarded as standalone manuscripts. Therefore, these two chapters have their own introduction, materials and methods, results, discussion, and conclusion sections. It can also be noted that these two chapters comprise of similarities as they focus on the same overarching aim of the study. The thesis chapters are presented as follows:

Chapter One provides a general introduction to the thesis, outlining the importance of water quality monitoring at a farm scale and the use of UAV-derived data in estimating TSS, CDOM and water temperature in a small water body. The research aims, objectives and research questions are included in this chapter.

Chapter Two serves as the first standalone manuscript. Through a global systematic review, the potential advancements in utilising drone technology along with machine learning algorithms, platform type, sensor characteristics, statistical metrics, and validation techniques for monitoring these water quality parameters are critically analysed. The study further discusses the strengths, challenges, and limitations of using UAVs in estimating water temperature, TSS, and CDOM in small water bodies. This review was used thereafter to inform the proceeding chapter on the methods, techniques and spectral indices used for monitoring and mapping surface water temperature, TSS and CDOM in small water bodies.

Chapter Three, the second manuscript, illustrates the practical application of drone-based remote sensing through a case study of the High Flight Farm dam in the uMngeni catchment. UAV-based remote sensing combined with machine learning techniques were used to monitor TSS, CDOM and water temperature of the small reservoir, and this chapter further addresses the challenges in agricultural water management and offers actionable insights for smallholder farming systems.

Chapter Four synthesises the findings of the study by integrating the findings and conclusions from both Chapter Two and Chapter Three. Additionally, this chapter addresses the limitations of the study and provides recommendations for future research.

CHAPTER 2: ASSESSING DRONE-BASED REMOTE SENSING FOR MONITORING WATER TEMPERATURE, SUSPENDED SOLIDS AND CDOM IN INLAND WATERS: A GLOBAL SYSTEMATIC REVIEW OF CHALLENGES AND OPPORTUNITIES (PAPER 1)[1]

Abstract

Monitoring water quality is crucial for understanding aquatic ecosystem health and changes in physical, chemical, and microbial water quality standards. Water quality critically influences industrial, agricultural, and domestic uses of water. Remote sensing techniques can monitor and measure water quality parameters accurately and quantitatively. Earth observation satellites equipped with optical and thermal sensors have shown to be effective in providing the temporal and spatial data required for monitoring the water quality of inland water bodies. However, using satellite-derived data is associated with coarse spatial resolution and thus is unsuitable for monitoring the water quality of small inland water bodies. With the development of Unmanned Aerial Vehicles (UAV) and artificial intelligence, there has been significant advancement in remotely sensed water quality retrieval of small water bodies, which provides water for crop irrigation. This article presents the application of remotely sensed data from UAVs to retrieve key water quality parameters such as surface water temperature, total suspended solids (TSS), and Chromophoric Dissolved Organic Matter (CDOM) in inland water bodies. In particular, the review comprehensively analyses the potential and advancements in utilising drone technology along with machine learning algorithms, platform type, sensor characteristics, statistical metrics and validation techniques for monitoring these water quality parameters. The study discusses the strengths, challenges, and limitations of using UAVs in estimating water temperature, TSS and CDOM in small water bodies. Finally, possible solutions and remarks for retrieving water quality parameters using UAVs are provided. The review is important for future development and research in water quality for agricultural production in small water bodies.

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[1] **Pillay, S.J**.; Bangira, T.; Sibanda, M.; Kebede Gurmessa, S.; Clulow, A.; Mabhaudhi, T. Assessing Drone-Based Remote Sensing for Monitoring Water Temperature, Suspended Solids and CDOM in Inland Waters: A Global Systematic Review of Challenges and Opportunities. Drones 2024, 8, 733. https://doi.org/10.3390/drones8120733

Keywords: unmanned aerial vehicles, water quality monitoring, TSS, CDOM, machine learning algorithm, remote sensing

2.1 Introduction

Small storage water bodies are vital to human and aquatic life since they support ecosystem services that sustain water for agricultural irrigation, human and animal consumption, industrial uses, and biodiversity conservation (Matthews, 2015, Edokpayi et al., 2017, Bangira et al., 2019, Korsgaard and Schou, 2010, Adjovu, 2023, Bangira, 2024). However, rapid population growth, urbanisation, industrial and agricultural activities, and climate change have increasingly threatened water quality in vulnerable regions such as southern Africa (Adjovu, 2023, Duan, 2023).

According to Mangadzea et al. (2018) and Namugize et al. (2018), aquatic ecosystems in southern Africa are stressed due to unsustainable land use - land cover changes, deforestation of catchments, pollution, contaminated runoff from mines and agricultural pesticides, and inadequate catchment management and water laws. The demand for suitable water resources has prompted efforts from policymakers, the public and researchers to monitor and manage water quality in water bodies to ensure sustainable use (El Bilali and Taleb, 2020) and to achieve the targets of sustainable development goal 6 (SDG 6), which advocates for clean water and sanitation for all by 2030 (Nations, 2015).

Traditional in situ water sampling and ground measurements are time-consuming, costly and labour-intensive (O'Grady et al., 2021, Ahmed et al., 2020). In contrast, satellite-based remote sensing provides an alternative by integrating remotely sensed data acquired by multispectral and thermal sensors for large-scale monitoring of spatial and temporal changes in water quality parameters in inland water bodies (Cillero Castro et al., 2020, Azzam, 2022, Boamah, 2024). Different sensors on satellites measure the radiation at various wavelengths reflected from the water surface. These reflections can be used directly or indirectly to detect different water quality indicators. The optically active parameters, including Total Suspended Solids (TSS), Chromophoric Dissolved Organic Matter (CDOM), temperature and chlorophyll-a, can be directly derived from remote sensing reflection (Adjovu, 2023, Lo, 2023).

Conversely, non-optically active substances such as chemical oxygen demand, total nitrogen, electrical conductivity, pH, metals, and Escherichia coli (E. coli), which have no direct optical properties, can be derived using proxies or artificial intelligence (Sun et al., 2014, El Din et al., 2017). The principle behind water quality remote-sensing inversion is first to build a model using empirical data from water quality monitoring and corresponding data from remote sensing images (forward modelling), then use the model to obtain the temporal and spatial distribution of water quality parameters (Chen, 2021, Hou, 2023). Although positive outcomes have been achieved in estimating optically active parameters in small water bodies using Landsat (Ciancia, 2020), MODIS (Hamidi, 2017), MERIS (Campbell, 2011) and Sentinel satellites (Rahul, 2023), limitations still arise. Coarse spatial resolutions hinder the monitoring of small-scale water bodies, atmospheric interferences such as the presence of clouds, long revisit times, and data accessibility limitations, which have been mentioned in the literature as some of the challenges (Cillero Castro et al., 2020, Omondi, 2023).

Unmanned Aerial Vehicles (UAVs) or drones have recently emerged as a viable solution, providing ultra-high spatial resolution data suitable for capturing detailed information on water quality parameters in small inland water bodies (Xiao, 2022, Bangira, 2024, Mishra, 2023). UAVs offer an advanced, practical and near-real-time method for monitoring water quality parameters (Nhamo et al., 2018, Koutalakis et al., 2019, Xiao, 2022). Since drone technology is fairly recent, studies such as Cillero Castro et al. (2020) have utilised satellite data as a primary source of information and drone-based data as a form of validation when monitoring water quality in a reservoir in Spain. The performance of both platforms was evaluated, and there was an agreement when comparing the water quality parameter results from both platforms.

While agriculture is the major use of water stored in small water bodies (Bangira et al., 2019), this review focuses on three major water quality indicators for water suitable for irrigation, considering that they can be measured using remote sensing techniques. This study focuses on surface water temperature, Total Suspended Solids (TSS) and Chromophoric Dissolved Organic Matter (CDOM). Water temperature is the measure of the kinetic energy of water, expressed as degrees Celsius (°C). Changes in water temperature stem from changing climates, diurnal temperature changes, seasonal changes, precipitation and evaporation (Woolway et al., 2020, Adjovu, 2023). In agriculture, varying water temperatures from irrigated water sources lead to decreased crop yields since changing water temperatures directly impact soil temperatures, specifically for sensitive crops during growing stages (Rajagopalan et al., 2018). Meanwhile, Total Suspended Solids (TSS) are fine particles suspended in water, including bacteria, algae, mineral particles, and organic debris (Al-Abed, 2009, Khouni et al., 2021, Bhatti et al., 2021). An increase in the TSS in reservoirs stems from increased soil erosion and runoff containing organic and inorganic pollutants flowing into the reservoir (Bhatti et al., 2021).

Consequently, significant amounts of suspended sediments can affect drip, centre pivot and ditch irrigation systems (El Bilali and Taleb, 2020). Chromophoric Dissolved Organic Matter (CDOM) is a fundamental subsection of Dissolved Organic Matter (DOM). It comprises a combination of compounds, dissolved organic matter and nutrients stemming from polluted residential, agricultural and industrial runoff (Zheng et al., 2023). Zheng et al. (2023) further explain that CDOM reduces light penetration and limits the production of beneficial nutrients needed for crop growth. These parameters are crucial for assessing physical, chemical, and microbial degradation of water quality, especially for agricultural use. Furthermore, given the prevalent challenges of water scarcity in southern Africa, farmers require timely information on water quality to sustain agricultural production and avert hunger and poverty. This emphasises that the suitability of water needs to be monitored regularly to meet irrigation and environmental standards as well as human and animal consumption standards (Nhamo et al., 2018). Subsequently, by utilising drone-derived high spatial resolution information, farmers can make educated decisions about how to conduct their everyday activities and early warning systems for timely intervention, leading to resilience building and enhancing productivity and economic benefits (Nhamo et al., 2018, Bangira, 2024).

Therefore, this study aims to systematically review the literature on the utility of remotely sensed data for monitoring surface water temperature, TSS and CDOM in small inland water bodies, particularly at a farm scale. The objectives are to evaluate the progress, challenges and opportunities associated with implementing and utilising UAV-based remote sensing to monitor water quality. This review is organised into several key sections. Following the introduction of section 1, section 2 focuses on the methodologies used to analyse existing literature critically. Section 3 focuses on the results from the literature analysis, highlighting the progress made utilising drone-based remote sensing, spectral indices and machine learning algorithms for monitoring the water quality of inland water bodies. Finally, section 4 synthesises the study's results and provides insight into the limitations, research gaps and research directions for future work using UAV-based remote sensing for water quality monitoring.

2.2 Materials and methods

The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) approach and 27-point checklist were used to conduct a comprehensive literature search, reduce reporting biases, ensure transparency and provide an in-depth systematic review (Moher et al., 2009, Page et al., 2021). The PRISMA approach was applied across three stages: the literature search, data extraction and analysis. A structured search strategy using Boolean operators and a diverse set of keywords was implemented across five academic databases (Table 2.1) and study selection was documented using a PRISMA flow diagram (Figure 2.1). The 27-item PRISMA checklist was also consulted to guide the reporting of review objectives, inclusion criteria, data handling and the synthesis. While the full checklist was not reproduced in this study, its principles informed the review structure and aided in minimising reporting bias.

2.2.1 Literature search

The initial step of the literature search was to identify keywords, terms and phrases about the scope of the intended study (Sibanda et al., 2021, Bangira et al., 2023). These keywords and phrases, along with Boolean operators such as "AND", “OR”, and “NOT” to form search strings which retrieved relevant publications were put into five search engines, namely, SCOPUS, Web of Science, Google Scholar, IEEE Xplore and Science Direct, and filtered to ensure relevant literature about the mapping and monitoring of water quality in inland water bodies was retained (Bangira et al., 2023). The Boolean operators aided in determining inclusive/exclusive criteria for each search string, which were restricted to keywords, titles, and abstracts of relevant literature. The search covered the period from 1980-2023, and 702 articles were retained from the five search engines (Table 2.1).

Table 2.1. Search strings for this review are made from keywords and Boolean operators.

Search engine	Search criterion	Total number of articles
Web of Science	TS=(“unmanned aerial vehicles” OR “drones” OR “UAVs” OR “remote sensing”) AND (“water quality monitoring” OR “inland water quality”) AND (“water bodies” OR “dams” OR “rivers” OR “reservoirs”) AND (“TSS” OR “suspended sediment” OR “temperature” OR “CDOM”) NOT (“sea water” OR “coastal water”)	328

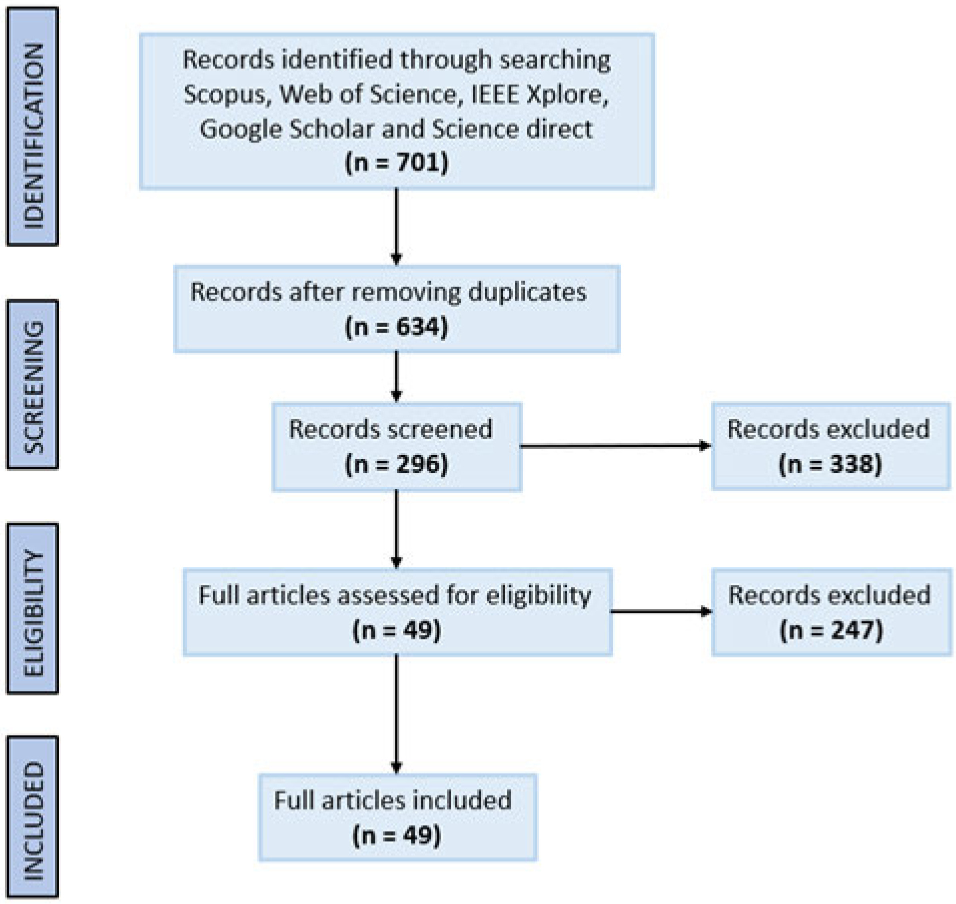
Google Scholar	(“unmanned aerial vehicles” OR “drones” OR “UAVs” OR “UAS”) AND (“water quality monitoring” OR “water quality assessment” OR “inland water quality”) AND (“dams” OR “reservoirs”) AND (“remote sensing”) AND (“TSS” OR “CDOM” OR “temperature” OR “Chromophoric dissolved organic matter” OR “suspended sediments”) AND (“machine learning algorithms” OR “regression algorithms”) NOT (“coastal waters” OR “ocean water”)	165
Scopus	(TITLE-ABS-KEY(“Unmanned aerial vehicles” OR “drones” OR “UAVs” OR “UAS”) AND (“water quality monitoring” OR “water quality assessment” OR “inland water quality”) AND (“water bodies” OR “dams” OR “reservoirs” OR “rivers”) AND (“TSS” OR “suspended sediment” OR “CDOM” OR “Chromophoric dissolved organic matter” OR “temperature”) AND NOT (“coastal waters” OR “groundwater”)	136
Science Direct	((“unmanned aerial vehicles” OR “drones” OR ‘UAVs”) AND (“water quality imaging” OR “monitoring”) AND (“TSS” OR “CDOM” OR “temperature”) NOT (“seawater”))	57
IEEE Xplore	(“All Metadata “unmanned aerial vehicles OR “All Metadata “drones OR “All Metadata “UAVs) AND (“All Metadata “water quality monitoring OR “All Metadata “inland water quality) AND (“All Metadata “TSS OR “All Metadata “CDOM OR “All Metadata “temperature) AND (“All Metadata “remote sensing) NOT (“All Metadata”: ocean water)	16
	Total number of Articles retained	**702**

All retrieved literature was exported into Endnote for further screening processes. The screening process was done in five stages. Firstly, 68 duplicates were removed since similar search terms can result in the same papers appearing across multiple search engines. The second step involved excluding 12 papers not written in English and 43 papers not identified as journal articles (such as conference proceedings). Thirdly, the abstracts of the remaining articles were read. A total of 282 papers which conducted predictive modelling, observed coastal regions and those which did not fit the scope of the study were excluded. Finally, 297 full-length articles were downloaded and exported into an Excel spreadsheet for further screening. Upon the last stage of screening, the inclusion criteria focused on selecting articles which:

1. Monitored any of the three specific parameters of TSS, CDOM or temperature

2. Involved the utilisation of unmanned aerial vehicles as a platform to aid remote sensing techniques

This resulted in 247 articles being excluded (Figure 2.1) since they focused solely on satellite-based remote sensing, focused exclusively on monitoring other water quality parameters outside of the specified parameters, utilised UAVs for groundwater monitoring and since numerous articles utilised UAVs to collect water samples rather than a platform for remote sensing sensors. After that, the final 50 articles were thoroughly read, and valuable characteristics were extracted and recorded.


IDENTIFICATION
SCREENING
ELIGIBILITY
INCLUDED
Records identified through searching Scopus, Web of Science, IEEE Xplore, Google Scholar and Science direct
(n = 701)
Records after removing duplicates
(n = 634)
Records screened
(n = 296)
Records excluded
(n = 338)
Full articles assessed for eligibility
(n = 49)
Records excluded
(n = 247)
Full articles included
(n = 49)

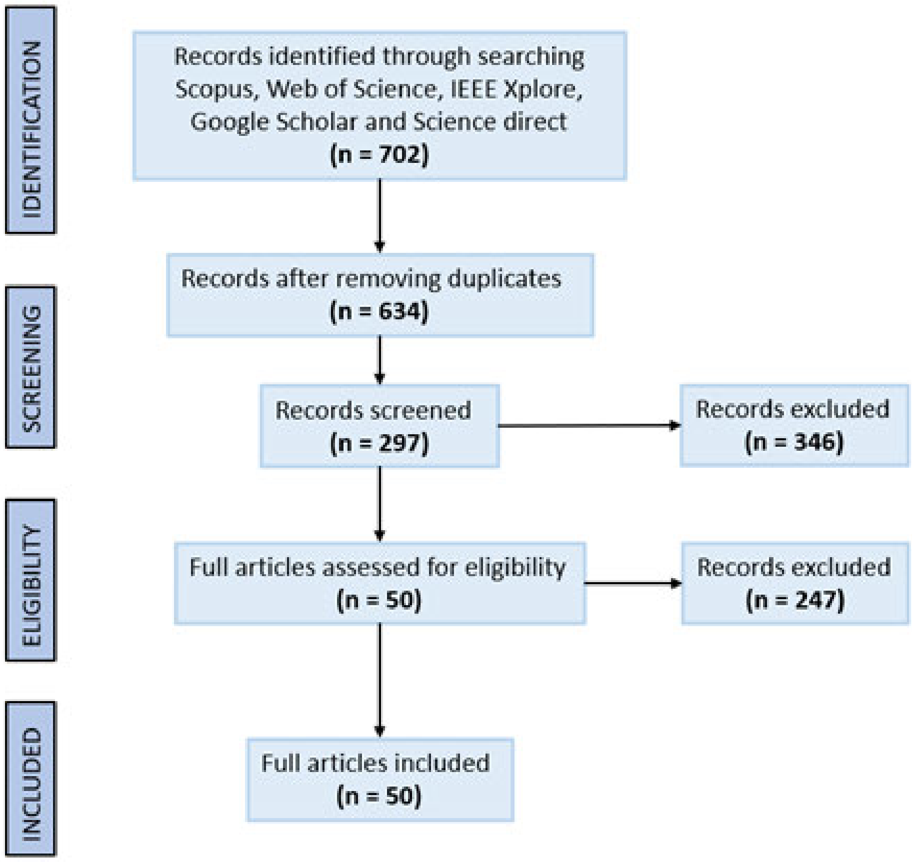


Figure 2.1 Selection of the studies considered in this review.

2.2.2 Data extraction

During the data extraction process, the previously created spreadsheet was used to record bibliometric data such as author names, year of publication, title of article, abstract and keywords from each article, along with characteristics such as the study site or country, type of water body, scale of water body, water quality parameter, platform type, sensor type, in-situ validation techniques, algorithms or models and statistical metrics used. This captured information highlighted the existing gaps and the progress made when referring to the use of UAVs in water quality monitoring at a regional scale.

2.2.3 Data analysis

Both quantitative and qualitative analyses were performed on the identified literature. A simple frequency analysis was performed for the quantitative assessment, while trend analysis was used to determine the qualitative characteristics of the literature. Additionally, this method was carried out to evaluate the advancements of UAVs for monitoring water quality by statistically assessing the occurrence and co-occurrence of key terms using VOS viewer software (Sibanda et al., 2021). The VOS viewer software was adopted for text mining and displaying bibliometric maps of key terms relating to the use of drone technology for water quality monitoring (Eck and Waltman, 2010). Studies that have utilised the software, such as Bangira et al. (2019), explain that it is advantageous in showcasing the current status of water quality research, developing trends, and most cited authors. It is useful for forecasting the future direction of disciplines and research themes. Once the screening and data extraction processes were complete, the articles' titles, keywords and abstracts were imported into the VOS viewer program to commence text mining. These results highlighted recurring key terms throughout the selected literature.

2.3 Results

2.3.1 Spatial distribution of UAV-based literature for water quality monitoring

The spatial distribution of the identified literature is depicted in Figure 2.2. More research has been conducted in the USA, Latin America, Europe and South-East Asia compared to Africa and Southern Africa. The USA and China had the highest number of 12 UAV-based articles monitoring TSS, Temperature and CDOM. This was followed by Brazil having four articles, Spain having three, India and South Korea having two, and countries such as South Africa, Namibia, Zimbabwe, Malawi, The United Kingdom and Chile having one article. Figure 2.2 also displays that the region of Southern Africa only accounted for 6.3% of the selected literature compared to South Asia, which accounted for 50%, and North and South America, which accounted for 25% and 10.4%, respectively. It is also apparent that no study in Africa's West, North and Central regions used UAV-based remote sensing to monitor TSS, temperature, and CDOM in water sources.

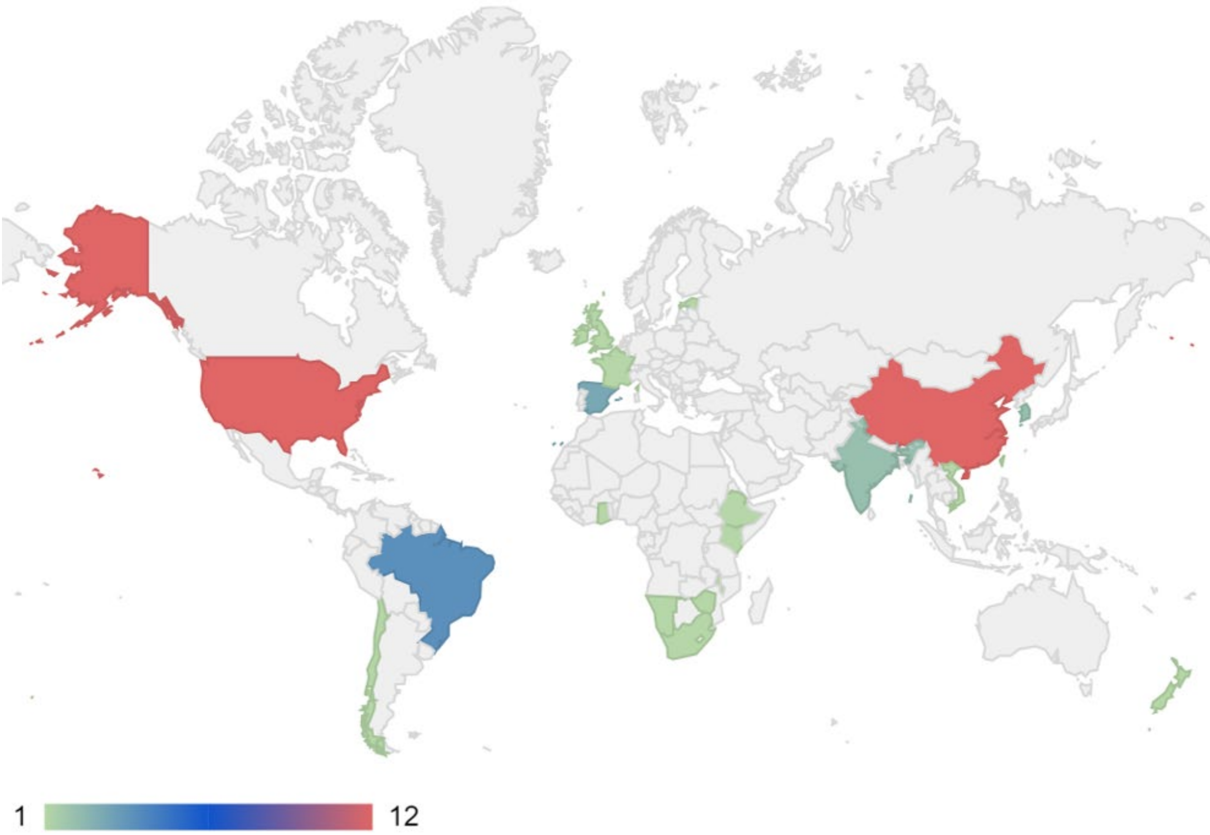


Figure 2.2 Spatial distribution of UAV-based remote sensing studies focused on monitoring surface water temperature, TSS and CDOM (Compiled by author)

2.3.2 Keyword analysis

Figure 2.3 highlights the important terms from the selected articles' titles, keywords and abstracts. Text mining was used to illustrate the evolution and direction of research, and four clusters were evident. Looking at each cluster in depth, it is visible that the keywords from cluster 1 are ‘parameter’, ‘Unmanned Aerial Vehicle’, ‘machine learning’ and ‘random forest’, which highlight what aspect of water quality is being measured, the remote sensing platform used as well as the processes used to understand and interpret UAV derived data. Cluster 2 highlights keywords such as ‘performance’, ‘water sample’, ‘lake’, ‘drone’, ‘UAV’, ‘RMSE’ (Root Mean Square Error), ‘USA’ and ‘temperature’. This suggests linkages between the performance of drone technology and in-situ data taken from water samples. It also highlights the major drone technology advancements in the United States of America compared to the rest of the world. Cluster 3 emphasises words such as ‘sensor’, ‘reservoir’, ‘estimation’, ‘mapping’, ‘TSS’, ‘case study’ and ‘chlorophyll’, suggesting links to water quality monitoring and highlighting the most optically active water quality parameters which can be detected by remote sensing. Finally, cluster 4 highlights keywords like ‘water’, ‘sentinel’, ‘Landsat’, ‘correlation’, ‘total nitrogen’, ‘total phosphorus’, ‘organic matter’ and ‘human activity’. This emphasised the use of satellite-based remote sensing to determine water quality parameters. Satellite remote sensing terminology stems from studies that observed UAV and satellite-derived data to analyse the selected water quality parameters. In such cases, UAV-based data was validated against satellite data from Sentinel and Landsat.

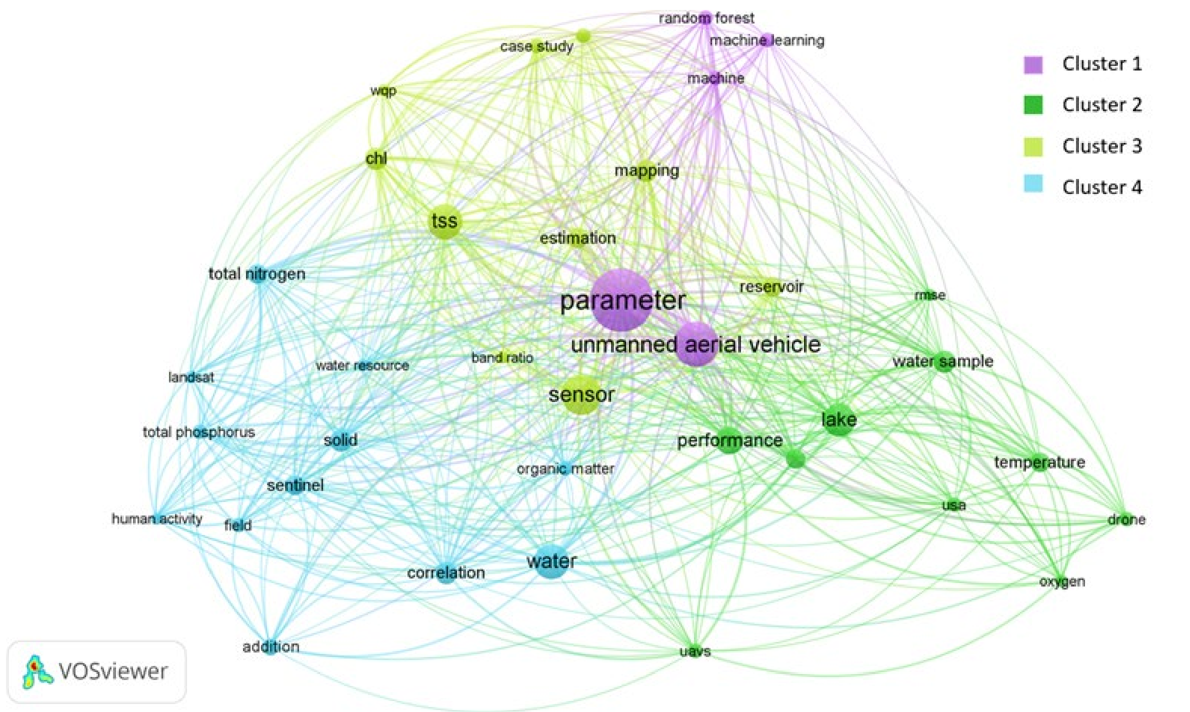


Figure 2.3 Topical concepts in monitoring water quality utilising UAV-derived remotely sensed data using information from abstracts, titles and keywords from literature.

2.3.3 Progress of remotely sensed water quality monitoring

Primarily, this review focused on using UAV-derived remotely sensed data to monitor surface water temperature, TSS, and CDOM. However, several studies utilising satellite-based remote sensing and comparing it with UAV-based remote sensing were selected, as they highlighted valuable techniques regarding temperature, TSS and CDOM. In these studies, UAV-based data, in-situ sampling, measurements and laboratory analysis were used to validate satellite data. Figure 2.4 illustrates that there has been much focus on the mapping and modelling of water quality using both remotely sensed satellite and UAV data, with the number of studies steadily increasing. Although remote sensing techniques have been popular since the 20th century and the selected range for this literature search was from 1980-2023, it is evident that there had only been a steep increase in published literature utilising UAV data since 2012. Before this, remote sensing was primarily conducted via satellites. When observing Figure 2.4, it is evident that Landsat 8 OLI has appeared more frequently within the selected studies and accounted for 13% of the total selected studies since UAV data was used for validation. For instance, a study by Xiao (2023) to monitor TSS across a lake utilised UAV-based data to calibrate satellite-based models directly. The results of this study exclaimed that the UAV-based data improved the satellite-based models due to the advances in spatial resolutions.

Additionally, 2021 and 2023 accounted for the remaining studies using UAV and satellite-based sensors such as Landsat 5, 7 and 9, ASTER, MODIS, MERIS and Sentinel 2. Alternately, Figure 2.4 highlights the significant increase in studies that ventured solely into using UAV-based data for mapping and monitoring water quality parameters. From 2020-2023, it is evident that there has been a significant increase in UAV-based studies, with 47% of the selected studies being found in this period. Additionally, the average number of UAV-based articles for these four years was eight articles per year.

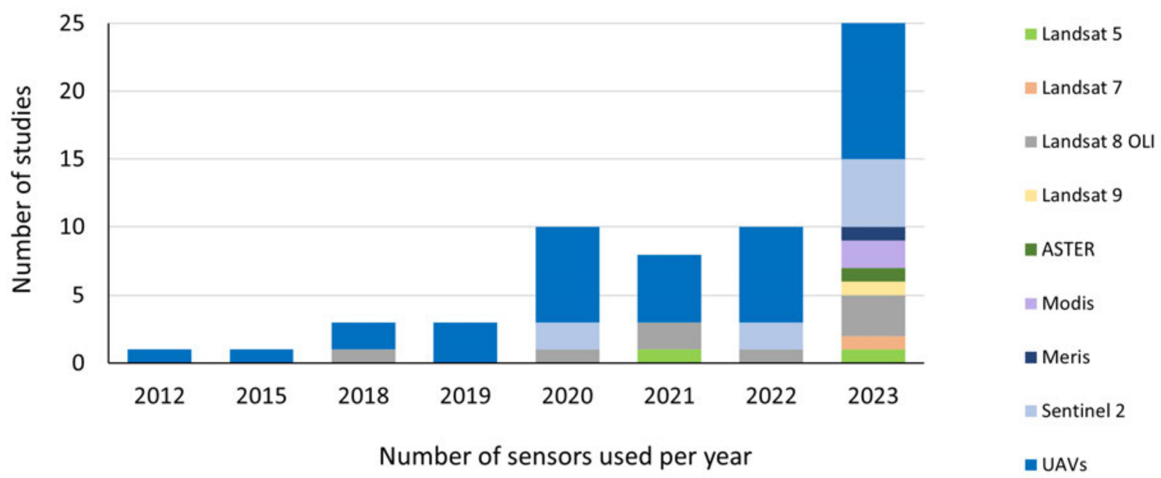


Figure 2.4 The frequency of studies per year based on both satellite sensors and UAVs

Figure 2.5 illustrates the parameters detected using UAV-based remote sensing only and the percentage they account for within the selected studies. Many studies focused on more than one parameter in conjunction with temperature, TSS and CDOM. For example, Womber et al. (2021) measured TSS with Turbidity and Secchi Disk Depth (SDD) in a large lake in Ethiopia. The authors found that changes in TSS concentrations influence Turbidity and SDD measurements, such that increased TSS resulted in increased turbidity in the lake. Furthermore, since the main objective of this review focused on TSS, surface water temperature and CDOM, these parameters appeared more frequently within the studies (Figure 2.5). Figure 2.5 shows that turbidity accounted for 13.6%, chlorophyll was 12%, temperature was 11.2%, TSS was 10.4%, CDOM was 4 %, etc. These parameters occurred more frequently in studies since they are said to be more 'optically active' than other water quality parameters. This means their particles scatter more light, making them easily detectable via UAV sensors (Gholizadeh et al., 2016). Parameters that accounted for less than 4% of the total studies were combined to form the 'other' category. These included salinity, total dissolved solids, algae content, dissolved organic carbon and Secchi disk depth, which comprised 10.4% combined. Temperature, TSS and CDOM formed a combined total of 25.6% of the selected literature.

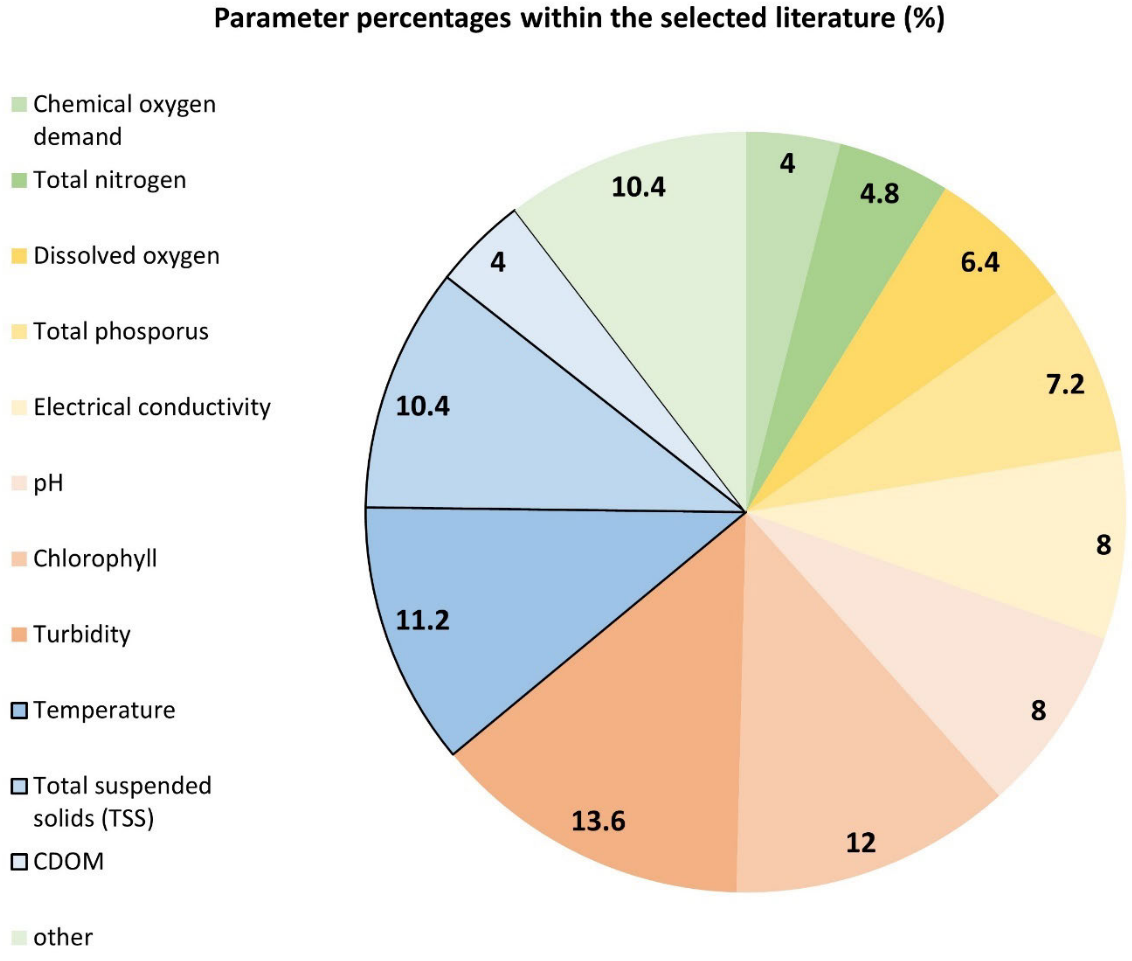


Figure 2.5 Percentage of each water quality parameter from the total number of selected studies.

2.3.4 Characteristics of sensors and UAV platforms

Figure 2.6 shows that various UAV platform types have been utilised throughout the years, including the DJI, the Octocopter, and the Sense fly eBee. The multicopter DJI UAV platform was dominantly used and accounted for 76% of the selected studies. For example, Lo (2023) utilised a DJI drone to estimate the temperature in a lake in China. It has been a popular choice of platform since 2020. The reason for the dominance of the DJI platform is that it is more compatible with many types of sensors and is better suited to surface water resource mapping, according to Brito (2019). The DJI platforms are also more cost-effective, and their taking-off and landing systems are advantageous. Conversely, the MD4-1000, Sense fly eBee, Hexacopter, Octocopter and 3DRSolo accounted for 4.8% individually.

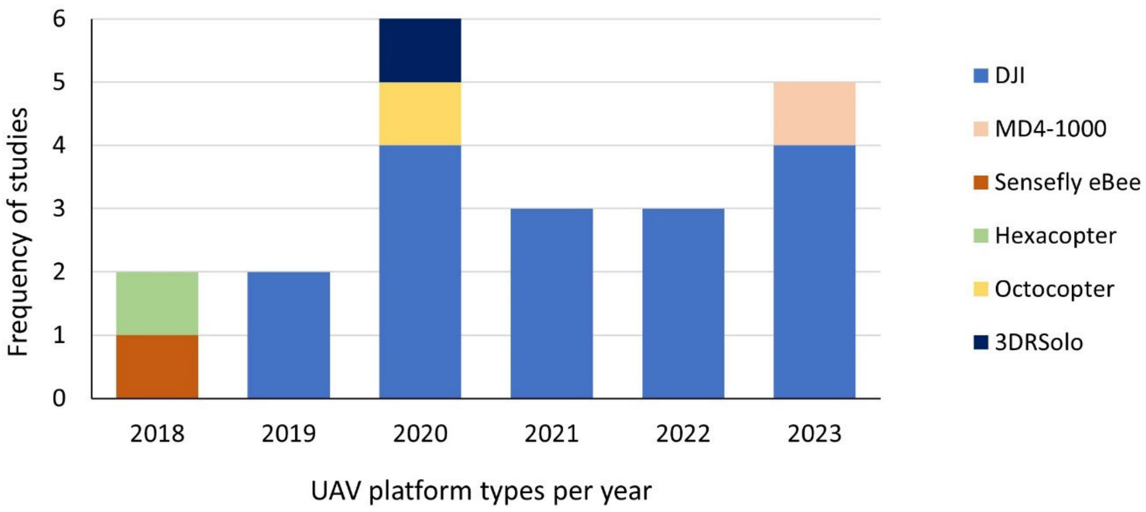


Figure 2.6 Frequency of studies relating to UAV platform types across a temporal scale

Regarding sensor types, it is apparent that multispectral sensors appeared more frequently compared to hyperspectral sensors when characterizing TSS and CDOM (Figure 2.7). Multispectral sensors are cost-effective compared to the hyperspectral sensors. Thus, they are widely used. The multispectral sensor captures imagery within the visible spectrum, at red, green and blue bands and outside of the visible spectrum at the near-infrared, red-edge and thermal infrared portions of the electromagnetic spectrum. Water temperature can be monitored using thermal infrared bands while CDOM uses blue and green bands and TSS uses red and near-infrared bands (Figure 2.7) Multispectral sensors were used to detect all three water quality parameters; however, thermal sensors were used predominantly to detect water temperature and TSS. In studies such as Mishra (2023), thermal sensors were used to analyse thermal stratification across water bodies which is influenced by fluctuating TSS concentrations which contribute to surface water heating.

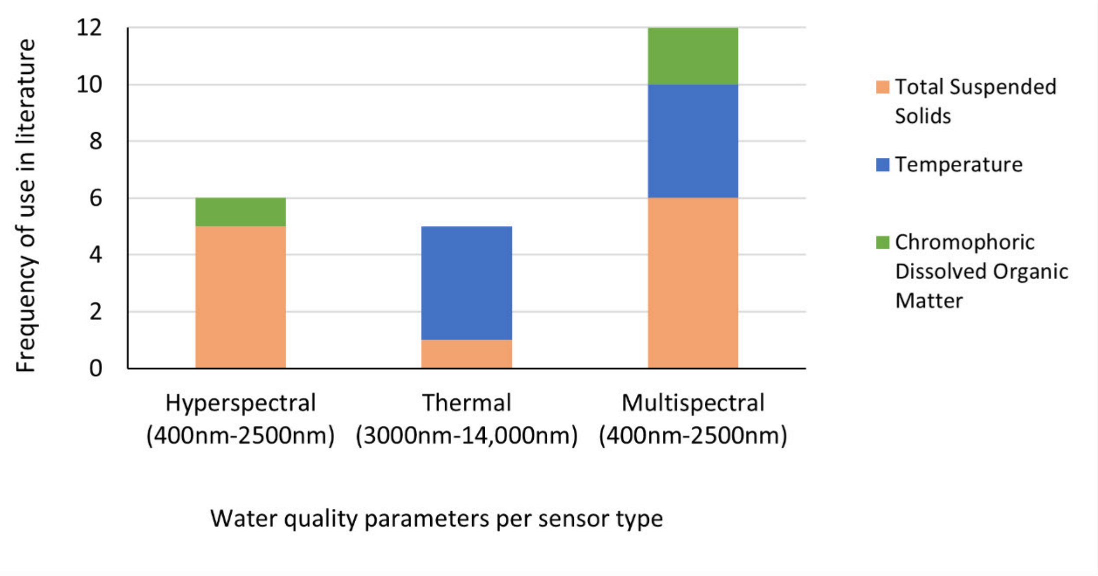


Figure 2.7 Frequency of sensor types used onboard drone platforms for detecting water temperature, TSS and CDOM.

2.3.5 Spectral indices used for estimating surface water temperature, TSS and CDOM in inland water bodies using sensors onboard UAVs

Studies have derived spectral indices algorithms using individual bands or multiple bands to predict the concentration of TSS, CDOM and water temperature in inland water bodies (Xiao, 2022). The combination of spectral indices and machine learning algorithms has significantly improved estimation and prediction models in estimating surface water temperature, TSS and CDOM in small water bodies (Sagan et al., 2020). Figure 2.8 shows indices commonly used to retrieve biophysical information about a study site by differentiating landcover spectral values. For example, these spectral indices were used to delineate between a water body and its surrounding vegetation, since surrounding vegetation influences runoff and erosion into water bodies, affecting the concentrations of TSS or CDOM. Furthermore, it is evident in Figure 2.8 that NDVI and NDWI appeared in most studies, accounting for 41.2% and 11.8%, respectively. These two indices were more frequently utilised due to their common red and near-infrared wavebands which are useful in detecting TSS and CDOM within water bodies (Choi, 2023).

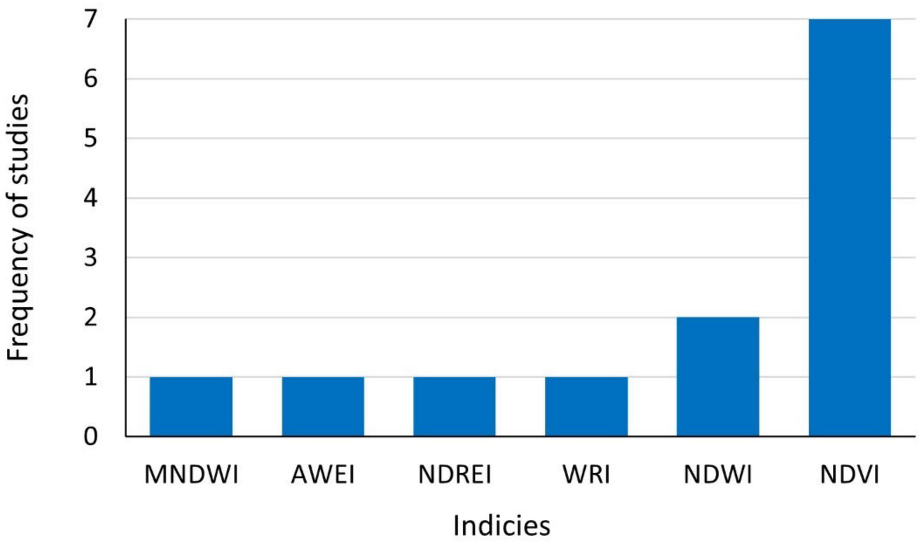


Figure 2.8 Indices used to delineate water bodies from surrounding vegetation (NDVI = Normalized Difference Vegetation Index; NDWI = Normalized Difference Water Index; WRI = Water Ratio Index; NDREI = Normalized Difference Red Edge Index; AWEI = Automated Water Extraction Index; MNDWI = Modified Normalized Difference Water Index)

Table 2.2 spectral indices derived from reflected or absorbed wavelengths that were used to quantify the concentration of TSS and CDOM and were (Sagan et al., 2020). Spectral indices for TSS are typically derived from the red and near-infrared portions of the electromagnetic spectrum due to suspended particles reflecting scattered light in these wavelengths. Spectral indices for CDOM are derived from wavelengths in the visible and ultraviolet portions of the electromagnetic spectrum due to light absorption in these wavelengths (Rahul, 2023, Larson, 2018). It is evident that for TSS, indices from Veronez et al. (2018) and Rahul (2023) obtained the highest R^2 values, while Kutser et al. (2005) and Fan (2014) obtained the highest R^2 values when quantifying CDOM concentrations. These high R^2 values can be attributed to feature enhancement since variations of spectral bands highlight specific TSS and CDOM characteristics (Sagan et al., 2020).

Furthermore, these spectral indices, can be combined with machine learning algorithms to produce models for testing and validating drone-derived data. A study done by Veronez et al. (2018) made use of spectral indices, utilising red and near-infrared portions of the electromagnetic spectrum as well as the Artificial Neural Network machine learning algorithm to predict the correlation between the indices and TSS and CDOM concentration values in an artificial lake. The results in Table 2.2 indicated that TSS x NDVI had an R^2 value of 0.65, TSS x NDWI had a value of 0.76, CDOM x NDVI had a value of 0.54 and CDOM x NDWI had a value of 0.59. Additionally, it can be noted that in literature, indices used to estimate surface water temperature were scarce since only one thermal band is used, compared to TSS and CDOM, which utilise a range of spectral bands.

Table 2.2 Spectral indices utilised in literature to characterize TSS and CDOM.

Water Quality parameter	Formula	R^2	Characteristics of the study area	Author and year
TSS	$TSS = 45.4 \times NDVI^2 + 43.1 \times NDVI + 20.9$	0.65	Small artificial lake in the South of Brazil	Veronez et al. (2018)
	$TSS = 68.7 \times NDWI^2 - 111.2 \times NDWI + 56.1$	0.76		
	$TSS = 151.2 + (384 \times (RE)) + \left(173.9 \times \left(\frac{G}{R}\right)\right)$ Where G is the green band (480-520nm) and R is the red band (640-680nm)	0.60	Stream is located in Alabama, USA	Larson (2018) Prior (2021)
	$TSS = 142.7 - \left(53.8 \times \left(\frac{R}{RE}\right)\right)$ Where R is the red band (640-680nm) and RE is the red-edge band (730-740nm)	0.60		
	$TSS = 8133.15 - 11002.9 \times \frac{B7}{(B6 + B8A)}$ Where B7 is 783 nm, B6 is 740 nm and B8A is 865 nm	0.73	Lake situated in Tamil Nadu, India	Rahul (2023)
CDOM	$CDOM = 244.9 \times NDVI^3 + 186.2 \times NDVI^2 + 7 \times NDVI + 21.8$	0.54	Small artificial lake in the South of Brazil	Veronez et al. (2018)
	$CDOM = 2119.5 \times NDWI^3 + 4559.1 \times NDWI^2 - 2760.4 \times NDWI + 603.6$	0.59		
	$aCDOM\ (420) = 5.20x^{-2.76}$ Where aCDOM (420) is the absorption of CDOM at 420 nm	0.84	Lake located in Finland	Kutser et al. (2005)
	$CDOM = 0.89 \times \frac{\rho 700\ nm}{\rho 450\ nm} - 0.15$	0.83	River, located in the USA	Fan (2014)

Where ρ is the spectral reflectance at wavelengths 700nm and 450 nm

2.3.6 Machine learning algorithms

Machine learning algorithms offer great opportunities for assessing, classifying, and predicting surface water temperature, TSS and CDOM in water quality studies for small inland water bodies using remotely sensed data acquired by sensors onboard UAVs. Figure 2.9 shows that linear regression (LR), empirical methods, random forest classification (RF), support vector machines (SVM), artificial neural networks (ANN), XGBoost, deep neural networks (DNN) and gradient boost decision trees (GBDT) were the most used algorithms. Linear regression appeared more frequently than other statistical methods 27.5% of the total articles.

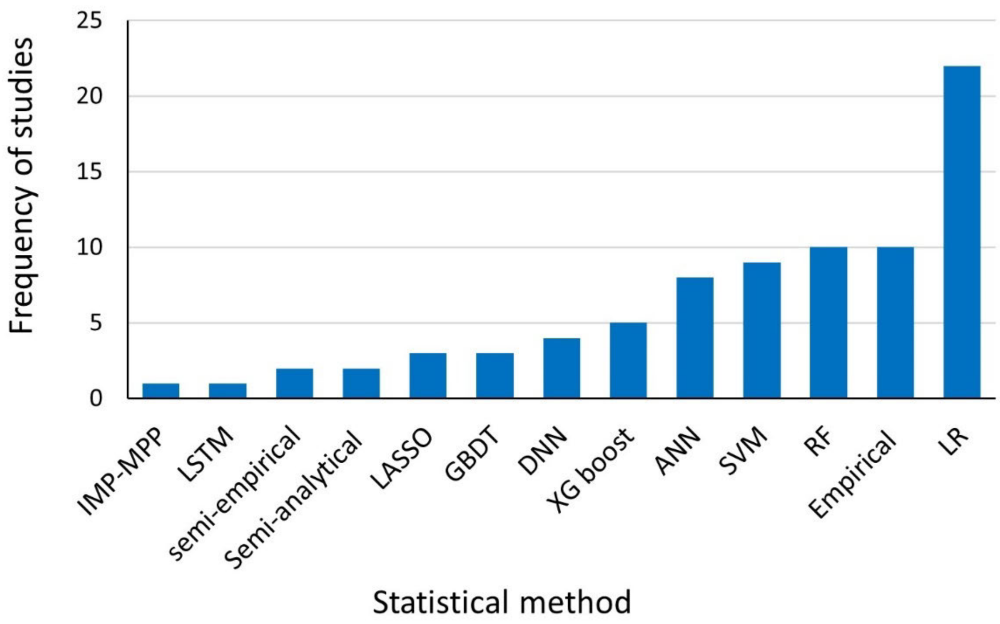


Figure 2.9 Machine learning algorithms used to detect and map surface water temperature, TSS and CDOM. (IMP-MPP = improved matching pixel by pixel; LSTM = Long Short-Term Memory; LASSO = Least Absolute Shrinkage and Selection Operator; GBDT = Gradient Boost Decision Trees; DNN = Deep Neural Networks; ANN = Artificial Neural Networks; SVM = Support Vector Machines; RF = Random Forest; LR = Linear Regression)

The random forest and empirical methods (polynomial and logarithmic regression models) appeared in 12.5% of the total articles. SVM and ANN appeared in 11.25% and 10%, respectively. Each of the remaining algorithms, such as IMP-MPP, LSTM, Semi-empirical, Semi-analytical, LASSO, GBDT, DNN and XG Boost, appeared in less than 7% of the total number of articles.

Fifty articles were chosen as case studies to identify further and explain algorithmic trends. Although the selected articles provided valuable information about monitoring surface water temperature, TSS and CDOM in small water bodies, not all of these articles solely utilised drone remotely sensed data or stated the validation techniques used. Approximately 35% of the selected articles utilised satellite-based remote sensing and only used drone-derived data as a validation technique. Moreover, 40% of the articles omitted information about in-situ data collection approaches, the statistical methods used or root mean square error (RMSE), resulting in the error assessment (R^2) being considered only. For this reason, these articles were excluded from the case studies (Table 2.3).

Table 2.3 consists of case studies from various regions across the globe, emphasising the statistical methods used for estimating each of the three water quality parameters (temperature, TSS and CDOM), as well as the in-situ data collection technique used and the error assessment (R^2). For TSS, several studies were conducted in South America and across Asia. These studies utilised the standard APHA weighing method to analyse field-collected water samples, as well as colorimeters and a TriOS RAMSES for spectro-radiometric data. These techniques were utilised as validation techniques. Alternately, these studies used varying statistical methods and machine learning algorithms. For instance, a study by Wei et al. (2019) utilised the Support Vector Machine algorithm to estimate TSS from hyperspectral UAV imagery and produced an R^2 value of 0.96. Similarly, the study by Olivetti (2020) utilised empirical and semi-empirical equations and models to estimate TSS from multispectral UAV imagery, resulting in an R^2 value of 0.94. Furthermore, Saenz et al. (2015) used linear regression to produce an R^2 value of 0.887.

Table 2.3 Case studies used to emphasise the statistical methods used for estimating temperature, TSS and CDOM from drone-derived data and their error assessment (R^2).

Title	Location of the study	Parameter	In-situ data collection technique	Statistical Technique	Fit error metric (R^2)	Author and year
Evaluation of surface water quality of Ukkadam Lake in Coimbatore using UAV and Sentinel-2 multispectral data	India	TSS	Colorimeter	Linear regression	0.86	Rahul (2023)
Evaluation of water quality based on UAV images and the IMP-MPP algorithm	China	TSS		IMP-MPP algorithm	0.825	Ying (2021)
Low-Cost Unmanned Aerial Multispectral Imagery for Siltation Monitoring in Reservoirs	Brazil	TSS	TriOS RAMSES spectroradiometer	Empirical and semi-empirical models	0.94	Olivetti (2020)
A method for chlorophyll-a and suspended solids prediction through remote sensing and machine learning	Brazil	TSS	APHA standard weighing method	RF	0.81	Silveira-Kupssinskü (2020)
Machine learning models applied to TSS estimation in a reservoir using a multispectral sensor onboard to RPA	Brazil	TSS	APHA standard weighing method	SVM	0.869	Dias (2021)
Proposal of a method to determine the correlation between total suspended solids and dissolved organic matter in water bodies from spectral imaging and artificial neural networks	Brazil	TSS	APHA standard weighing method	ANN	0.77	Vernonez (2019)
Local algorithm for monitoring total suspended sediments in micro-watersheds using drone and remote sensing applications. Case study: Teusaca River, La Calera, Columbia	Columbia	TSS	Sampling and lab analysis	Linear regression	0.887	Saenz et al. (2015)
Machine learning algorithm inversion experiment and pollution analysis of water quality parameters in urban small and medium-sized rivers based on UAV multispectral data	Korea	TSS	APHA standard weighing method	RF	0.635	Hou (2023)

Inland waters suspended solids concentration retrieval based on PSO-LSSVM for UAV-borne hyperspectral remote sensing imagery	China	TSS	Sampling and lab analysis	SVM	0.96	Wei et al. (2019)
Drone with a thermal infrared camera provides high-resolution georeferenced imagery of the Waikite geothermal area, New Zealand	New Zealand	Temp		Linear regression	0.98	Harvey et al. (2016)
Monitoring Phytoplankton Biomass and Surface Temperatures of Small Inland Lakes by Multispectral and Thermal UAS imagery	USA	Temp	Multiprobe	Linear regression	0.31	Bartel (2021)
Medium-Sized Lake Water Quality Parameters Retrieval Using Multispectral UAV Image and Machine Learning Algorithms: A Case Study of the Yuandang Lake, China	China	Temp	Multiprobe	Gradient boosting	0.75	Lo (2023)
Urban Land Surface Temperature Monitoring and Surface Thermal Runoff Pollution Evaluation Using UAV Thermal Remote Sensing Technology	China	Temp	Thermometer	Linear regression	0.83	Xu (2021a)
The impacts of environmental variables on water reflectance measured using a lightweight unmanned aerial vehicle (UAV)- based spectrometer system	Canada	CDOM	In-situ sensor	Linear regression	0.61	Zeng et al. (2017)
UAV Multispectral Image-Based Urban River Water Quality Monitoring Using Stacked Ensemble Machine Learning Algorithms—A Case Study of the Zhanghe River, China	China	CDOM	In-situ sensor	XGBoost	0.92	Xiao (2022)
Remote sensing Estimation of CDOM and DOC with the Environmental implications for Lake Khanka	China	CDOM	Spectrophoto meter	GBDT	0.95	Qiang et al. (2023)

Estimation of the Biogeochemical and Physical Properties of Lakes Based on Remote Sensing and Artificial Intelligence Applications	Estonia	CDOM		XGBoost	0.92	Toming et al. (2024)
Underwater Use of a Hyperspectral Camera to Estimate Optically Active Substances in the Water Column of Freshwater Lakes	Germany	CDOM	Fluorometer	Empirical and semi-empirical models	0.47	Seidel et al. (2020)
Estimation of Water Quality Parameters in Oligotrophic Coastal Waters Using Uncrewed-Aerial-Vehicle-Obtained Hyperspectral Data	Croatia	CDOM	Fluorometer	Linear regression	0.92	Divi´c et al. (2023)
Autonomous learning of new environments with a robotic team employing Hyperspectral Remote sensing, Comprehensive in-situ sensing and machine learning	USA	CDOM	In-situ sensor	Linear regression	0.97	Lary et al. (2021)

Studies on CDOM were conducted in North America, Europe, and Asia, where in-situ measurements were primarily taken using in-situ CDOM sensors, fluorometers, and a spectrophotometer. Additionally, these studies utilised different statistical methods and algorithms such as linear regression, XGBoost, Gradient boost decision trees (GBDT) and empirical methods. The studies compiled by Lary et al. (2021), Divi´c et al. (2023) and Zeng et al. (2017) utilised linear regression to estimate CDOM from UAV imagery and resulted in an R^2 value of 0.97, 0.92 and 0.61, respectively. Following this, other studies utilised Gradient boost decision trees, XGBoost, and empirical methods to estimate CDOM in water sources, producing values of 0.95, 0.92, and 0.92, respectively.

Finally, when looking at temperature, 50% of the studies took place in China and utilised in-situ thermometers and multiprobes. Additionally, most studies utilised linear regression, resulting in the highest R^2 value of 0.98, as seen in the study by Harvey et al. (2016). Furthermore, Table 2.3 highlights the statistical methods most used for TSS, CDOM, and temperature estimation, which happens to be linear regression, emphasised in Figure 2.9. This is due to linear regression being easier to understand and implement. Additionally, this can be said for empirical methods that utilise spectral band rations and indices to assess water quality parameters based on remotely sensed data from drones. Furthermore, Figure 2.10 was generated to assess the magnitude of performance of the most commonly used algorithms and statistical methods from the case studies.

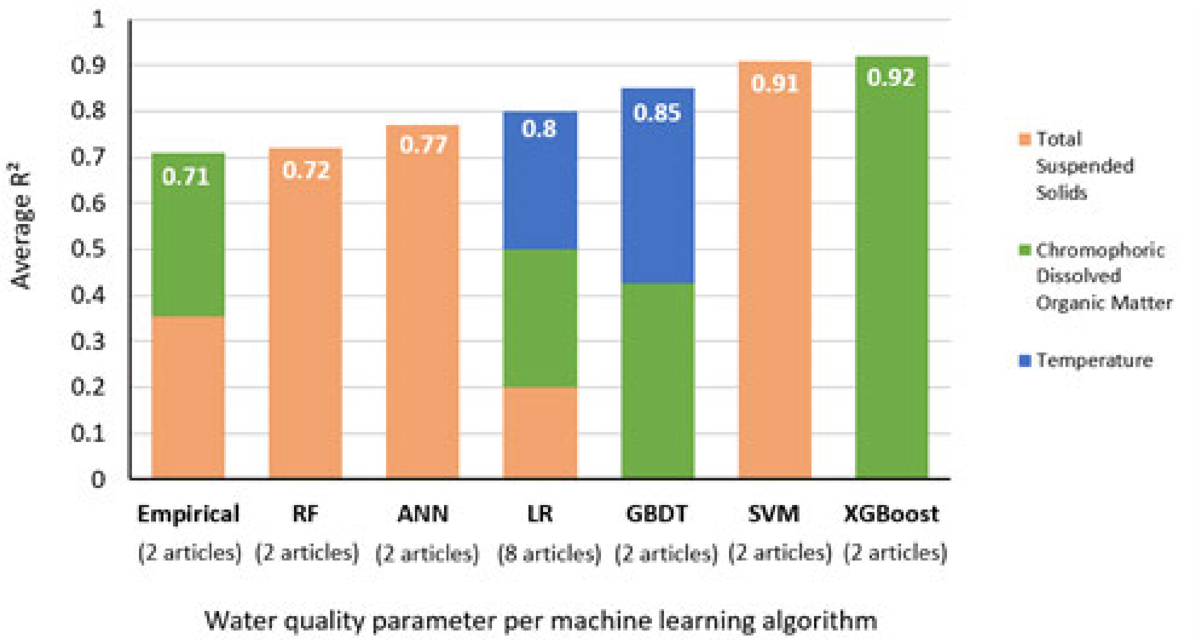


Figure 2.10 Average error assessment of machine learning algorithms

Figure 2.10 highlights the average error assessment of machine learning algorithms, their use for estimating TSS, CDOM, and surface water temperature, and how many articles appeared. With eight studies utilising it, linear regression was the most widely used technique for estimating all three water quality parameters, yielding an average error of assessment value of 0.8. Nevertheless, XGBoost was utilised in two articles for CDOM estimation and had the greatest average R^2 of 0.92 across the case studies. Alternately, SVM, ANN, and RF algorithms obtained average R^2 values of 0.91, 0.77, and 0.72, respectively. These algorithms were used solely to estimate TSS in the case studies. GBDT and empirical methods obtained average R^2 values of 0.85 and 0.71, respectively, and were utilised to estimate CDOM. Furthermore, all algorithms and statistical methods obtained average error assessment values above 0.7. This indicates good performance since values closer to 1 represent higher estimation accuracies.

2.4 Discussion

2.4.1 Progress in the remote sensing of temperature, TSS and CDOM using drone technologies

In recent years, UAV-based remote sensing has significantly monitored TSS, CDOM and surface water temperature in small water bodies. However, when looking at the spatial distribution of these efforts, it is evident that there has been much effort in the USA and China (Figure 2.2) since the earliest drone technologies began in the 1850s in Europe, the USA, and China (Sibanda et al., 2021). These are considered "technologically advanced" nations compared to many other regions, such as Africa, which lack the resources and skilled labour to conduct such research. However, the use of drone technology has spread worldwide over the past decade (Sibanda et al., 2021). Furthermore, Sibanda et al. (2021) emphasised that the utility of drone technology in southern Africa was still rudimentary; however, a few years later, there has been significant progress illustrated by a sharp increase in the number of studies utilising drone technology for TSS, water temperature and CDOM, specifically in South Africa, Zimbabwe and Namibia (Figure 2.2).

Over the past decades, satellite-based remote sensing has been the dominant and conventional earth observation approach (Gitelson et al., 1993). However, using UAVs has recently been demonstrated to be a more effective and reliable technique, especially when dealing with small inland water bodies, since they offer fine-resolution data in near-real time. For this reason, many identified literature sources compared satellite and drone-based techniques. These studies use drone-based data to validate satellite-based data for water temperature, TSS and CDOM. As depicted in Figure 2.4, UAVs appeared more frequently in the literature since this review focused on the application of drone technologies. However, numerous widely used satellite sensors also appeared in conjunction with UAVs. These were predominantly Landsat, Sentinel 2 MSI, MODIS and MERIS. When looking specifically at satellite sensors, it is evident that Landsat 8 operational land instrument (OLI) appeared in numerous studies compared to the other sensors (Figure 2.4). According to Gholizadeh et al. (2016), this is due to Landsat being the longest free-supplying mission of remotely sensed data and being the best suited for identifying water quality parameters. Furthermore, satellite sensors are prone to limitations such as cloud cover and lagged return times. They produce coarser resolution images that are inadequate for water quality monitoring in small inland dams (Acharya, 2022).

Subsequently, the results from this review suggest that the most commonly used UAV platform has been the DJI drone due to its compatibility and versatility (Figure 2.6). This platform is relatively affordable, with supplies available globally and is user-friendly for commercial UAV operations since it provides high-resolution images (Yoakum, 2020, DJI, 2023). Along with this platform, multispectral imaging sensors are the most appropriate for water quality monitoring (Figure 2.7). However, the results indicated that several studies used hyperspectral imaging sensors compared to multispectral sensors. This is because hyperspectral sensors have hundreds of spectral bands compared to the 4-6 bands multispectral sensors have. These multispectral bands are also narrower, allowing for increased sensitivity to water quality parameters such as TSS, CDOM and surface water temperature (Kim et al., 2022). However, hyperspectral is very costly and has a greater weight, thus requiring bigger UAV platforms.

Furthermore, remote sensing-based approaches for the estimation of temperature, as well as TSS and CDOM, involve establishing relations between these parameters and the spectral properties of remote sensing images. According to Adjovu (2023), these main approaches include empirical, analytical, semi-empirical and artificial intelligence methods. Adjovu (2023) further explains each method, starting with empirical methods, which utilize linear statistical relationships derived from measured remote sensing spectral properties and water quality parameters. This simple and straightforward approach has been used to estimate and retrieve water quality data effectively. Analytical methods involve the use of bio-optical and transmission models to simulate how light is spread in water bodies and the relationship between water quality parameters and their reflection. Since this method utilises models, it is considered more complex than the empirical method. Semi-empirical methods are a combination of empirical and analytical methods. In this method, the spectral characteristics of the water quality parameters are known, and the appropriate combination of wavebands is used as a correlate. The spectral radiance is recalculated to values above the surface irradiance reflectance and then, through regression techniques, related to the water quality parameters. Finally, Artificial Intelligence (AI) methods utilise an implicit algorithm approach that differs from the three other approaches. AI applications capture linear and nonlinear relationships compared with conventional statistical approaches and are the most advanced and complex of the approaches (Adjovu, 2023).

Table 2.3 shows that a variety of algorithms/regression approaches were used in the case studies to determine TSS, surface water temperature, and CDOM. Regarding TSS, Support

Vector Machines yielded the highest R^2 value of 0.96, followed by empirical and semi-empirical approaches, which yielded the second-highest R^2 value of 0.94. For temperature, three of the four observed case studies utilised linear regression statistical approaches, yielding the highest R^2 values of 0.98. Furthermore, for CDOM, various techniques were used, including XGBoost Gradient Boost Decision Trees (GBDT) and linear regression, which yielded the highest R^2 of 0.97. Therefore, moving forward, these techniques can be combined with spectral bands and indices to produce models for testing and validating drone-derived data, which can be considered for use in further research.

2.4.2 Limitations of utilising drone technologies in monitoring TSS, CDOM and water temperature in small water bodies

Although drone technologies have been proven beneficial for monitoring water temperature, CDOM, and TSS, there are many limitations, specifically in southern Africa. One of the limitations is the cost of equipment. Although this technique is low-cost, acquiring a license, a suitable UAV platform, and various sensors can become costly, specifically when limited funding is available (Adjovu, 2023). Furthermore, these costs raise concerns about security, theft, and damage to equipment, which lead to the limited use of drone technology. Additionally, since the use of drone technology is still a novel approach for water quality monitoring in Southern Africa, there is a lack of skilled and trained technicians who can operate the drones over water bodies as well as a lack of trained professionals who can interpret the collected data (Adjovu, 2023).

Further challenges include connectivity issues since many parts of southern Africa lack network coverage. Technical challenges include limited battery efficiency, flight ranges, and limited altitudes of drones. Environmental challenges, such as the interference of drone technology on wildlife and challenges due to weather sensitivity, such as heavy rainfall periods experienced in Southern Africa during summer months, hinder drone flights. Furthermore, aviation restrictions and privacy concerns limit where drones can be flown.

2.4.3 Research gaps

While drone-based remote sensing for monitoring inland water quality has made great progress in recent years, numerous research gaps are still evident in the literature. The first gap is the limited use of UAVs for monitoring water temperature, TSS and CDOM in Africa. Through literature, it was highlighted that parameters such as chlorophyll content, total nitrogen and total phosphorus are more frequently monitored in small water bodies across other world regions. At the same time, only a very limited number of studies were done in Africa, particularly in southern Africa. This observation brought to light the inability of drone-based remote sensing to adjust its performance across various climatic zones, natural calamities like droughts, and water conditions, including turbidity, flow regimes, and vegetation interference. Additionally, little research has been done on smaller inland water bodies like reservoirs; most studies have concentrated on major lakes, rivers, and coastal locations. There were also clear gaps regarding the absence of field validation studies. Numerous studies have provided systematic reviews, overviews and reports regarding the advancements in drone technology; however, there is a shortage of field validation studies or case studies that have deployed drone technology to monitor water quality. This highlighted the underutilisation of advanced sensors such as LiDAR and Worldview2-3 to capture detailed water quality parameters and the lack of integration of in-situ measurements coupled with remote sensing to improve accuracy and reliability. The limitations of utilising drone technology, such as the cost, technical skills and regulatory challenges, limit real-time monitoring and reporting for immediate decision-making in water resource management. Subsequently, this emphasises gaps regarding interdisciplinary and collaborative research approaches. With minimal exploration of how drone-based remote sensing could be beneficial and accessible to farmers, local governments, and policymakers to generate actionable solutions for water management and water quality monitoring on a farm scale.

2.4.4 Future Research Directions

Future research is encouraged to enhance field validation techniques by building on the identified research gaps. Research is needed to create robust and standardized protocols for validating drone-based data and to ensure consistency and accuracy for different applications and uses in various industries. Additionally, hybrid methods that combine drone data with satellite imagery (from Worldview or Sentinel) and in-situ measurements can produce a comprehensive, multiscale view of the water systems being studied. Subsequently, increased research is needed to monitor less mainstream water quality parameters such as TSS and CDOM since these parameters are of great importance in the agricultural and industrial sectors. Since there is a lack of research done on small inland water bodies, future research is encouraged across these water bodies, considering they play a great role in the development of the region they occupy. These small water bodies are often utilised for agricultural and industrial purposes or for domestic uses, and further research into monitoring these water bodies could have great socio-economic benefits. Lastly, increased research efforts in Africa would be highly beneficial due to the continent's unique climatic zones, addressing water quality challenges and environmental sustainability.

2.5 Conclusion

This systematic review highlights the progress, advantages and disadvantages of utilising sensors onboard UAVs to monitor surface water temperature, TSS and CDOM in small inland water bodies. A comprehensive literature search was done by utilising the PRISMA guidelines, and through a transparent screening process, the literature was critically assessed for relevance and quality. This identified the overall trend of publications and the interlinkages between the characteristics of the sensors, techniques and validation methods. The results indicated that while significant progress has been made globally, there has also been an increase in progress made within southern Africa. The findings suggest that while the application of drone technologies in water quality monitoring is a fairly new technique, there is strong agreement when utilised as a validation technique along with satellite-based remote sensing. Through case studies, linear regression appeared as the most used statistical method, while all the average error assessment values (R^2) were above 0.7 for several other algorithms. This signified high accuracies for estimating water temperature, TSS and CDOM. Furthermore, this review synthesised the results and emphasised the importance of progress in water quality monitoring through UAV remote sensing techniques moving forward. Future research needs to account for the fact that effective mapping of water temperature, TSS and CDOM using UAVs is still rudimentary and, therefore, more research is needed to overcome the limitations as mentioned earlier, including the development of explicit methods and techniques and fusion of data from many sources. To address this, the proceeding chapter focuses on the practical implementation of utilising drone-based remote sensing to monitor TSS, CDOM and water temperature. Using the systematic review as a guide to formulate the appropriate methodology, a case study was conducted in the uMngeni catchment of South Africa. The transition from theoretical to practical application highlighted not only the advancements of drone-based remote sensing for water quality monitoring but also their real-world utility and effectiveness at a local scale.

CHAPTER 3: ASSESSING THE UTILITY OF DRONE TECHNOLOGY IN ESTIMATING SURFACE WATER TEMPERATURE, TOTAL SUSPENDED SOLIDS AND CHROMOPHORIC DISSOLVED ORGANIC MATTER IN RESERVOIRS: A CASE STUDY OF THE HIGH FLIGHT FARM DAM

Abstract

Water quality monitoring is a critical characteristic of environmental management, specifically in regions where water resources are under pressure due to climatic variability, population growth and land use changes. In South Africa, the sustainability of freshwater resources for irrigation uses is increasingly challenged by these factors, necessitating advanced, near-real-time approaches to assess and monitor key water quality parameters such as temperature, total suspended solids (TSS) and Chromophoric dissolved organic matter (CDOM). This study investigates the use of UAV-derived data for monitoring these water quality parameters within a small-scale reservoir within the uMngeni catchment of South Africa. Data collection involved a combination of in-situ measurements, laboratory analysis and UAV-based remote sensing using multispectral and thermal infrared sensors. In-situ measurements captured water temperature, TSS and CDOM concentrations from 30 sample points across the dam, while UAV-derived data provided high-resolution spatial coverage. Spectral indices such as the Specific Near-Infrared Index (SNIR) and Shortwave Band Reflectance Edge (SBRE) were used to characterise TSS, while the Normalized Difference Vegetation Index (NDVI), Green Normalized Difference Vegetation Index (GNDVI) and Green Chlorophyll Index (GCI) were used to characterise CDOM. These indices were instrumental in estimating and predicting TSS and CDOM concentrations by utilising machine learning algorithms, individual models and model ensembles. The model ensembles for both TSS and CDOM produced the lowest predictive errors, being (RMSE=30.50 mg/l and MAE=19.20 mg/L) and (RMSE=0.17 mg/L and MAE=0.12 mg/L) respectively. Although the model performance metrics were adequate, many limitations arose during this study, which are further elaborated on in future research recommendations.

Keywords: unmanned aerial vehicles, water quality monitoring, TSS, CDOM, machine learning algorithm, remote sensing

3.1 Introduction

South Africa's irrigation systems rely on diverse water sources, including lakes, rivers, rainfall, groundwater and man-made reservoirs and dams, to sustain its agricultural sector (El Bilali and Taleb, 2020). However, the quality of these water sources is a critical factor which determines their suitability for irrigation purposes. Poor water quality poses significant challenges to irrigation efficiency and crop health, as highlighted in various studies. For instance, Al-Abed (2009) and Bhatti et al. (2021) noted that high sediment loads in irrigation water can clog emitters in drip irrigation systems, reducing their efficiency and causing crop water stress. Similarly, floating particles such as sand and organic matter can impair the performance and longevity of irrigation networks (Al-Abed, 2009, Bhatti et al., 2021). In addition to physical contaminants, variations in water temperature present further challenges. As observed by Rajagopalan et al. (2018), cooler water sourced from downstream ends of reservoirs can adversely affect soil temperatures and crop yields, particularly for temperature-sensitive crops during critical growth phases, while extreme temperature fluctuations may also stress plant roots and result in irreversible damage (Feller and Irina, 2014).

Another critical concern in irrigation water quality is the presence of Chromophoric Dissolved Organic Matter (CDOM), a significant component of Dissolved Organic Matter (DOM). CDOM originates from residential, agricultural and industrial runoff and affects water clarity by reducing light penetration and limiting the availability of essential nutrients for crops (Zheng et al., 2023). Additionally, CDOM's ability to bind nutrients in water further disrupts the nutrient balance required for optimal plant growth (Guo and Marschner, 1995). Moreover, temporal and spatial fluctuations in water quality parameters such as total suspended solids (TSS), water temperature, and CDOM have far-reaching implications for agriculture, water resource management, and aquatic ecosystems (Khouni et al., 2021). Addressing these challenges is essential to ensure sustainable and efficient irrigation practices in South Africa's agricultural sector.

Recent technological advancements, particularly the use of Unmanned Aerial Vehicles (UAVs), offer promising solutions for monitoring and managing water quality. Equipped with advanced sensors, UAVs provide real-time, high-resolution spatial data that surpass the capabilities of satellite images (Nhamo et al., 2018). UAVs are especially effective in mapping small water bodies, which often serve as crucial irrigation sources for smallholder farmers (Khatri-Chhetri. A, 2016). Additionally, the integration of UAV-derived spectral indices and machine learning models offers a promising approach to overcome the limitations of traditional monitoring methods. Spectral indices, such as the Specific Near-Infrared Index (SNIR), Shortwave Band Reflectance Edge (SBRE), Normalized Difference Vegetation Index (NDVI), Green Normalized Difference Vegetation Index (GNDVI) and Green Chlorophyll Index (GCI) were used and leverage the reflectance properties of TSS and CDOM in specific spectral bands to estimate their concentrations remotely (Yépez, 2024, Adjovu, 2023).

Machine learning models, such as random forest, support vector machines and gradient boosting, enhance the predictive accuracy of these indices by accounting for complex, non-linear relationships among water quality parameters and environmental variables (Xu, 2021a, Yao, 2024). Furthermore, this study evaluates the performance of these models and indices in predicting TSS and CDOM concentrations by utilising performance metrics such as the root-mean-squared error (RMSE) and the Mean absolute error (MAE) and provides insights into their reliability and applicability for water quality monitoring.

This use of UAVs for water quality monitoring can mitigate crop stress and further address challenges such as algal blooms and thermal plumes which ultimately enhances the efficiency of irrigation systems. Furthermore, by delivering timely and accurate information on water quality parameters, UAVs empower farmers to make informed decisions regarding irrigation management (El Bilali and Taleb, 2020). The integration of UAVs into water quality assessment marks a transformative step for South Africa's agricultural sector, offering significant potential to improve resource management and resilience for smallholder farmers. This study aims to bridge the gap between traditional water quality monitoring and modern, technology-driven approaches. By examining the interactions among temperature, TSS, and CDOM and assessing the performance of UAV-based models and indices, this study contributes to the development of scalable and cost-effective solutions for water quality assessment in South Africa and beyond.

3.2 Methods and materials

3.2.1 Study site description

Situated in KwaZulu-Natal, South Africa, the uMngeni catchment spans 4349 km^2 and is home to one of the largest perennial rivers in the country (the uMngeni river), rising at the uMngeni vlei at an altitude of 1760m and draining into the Indian ocean (Ngubane et al., 2022, Namugize et al., 2018). The uMngeni catchment receives varying annual precipitation of approximately 650mm, whereby most high rainfall events occur during the summer months. Subsequently, the catchment experiences average annual temperatures ranging between 12-23 °C and average annual surface water evaporation rates between 1567 and 1737mm. Located in the upper regions of the uMngeni catchment is the High Flight farm dam. The dam is situated adjacent to cattle and potato farms and surrounded by vast agricultural landscapes (Figure 3.1). The dam spans 0.2 km^2 and is predominantly used for crop irrigation.

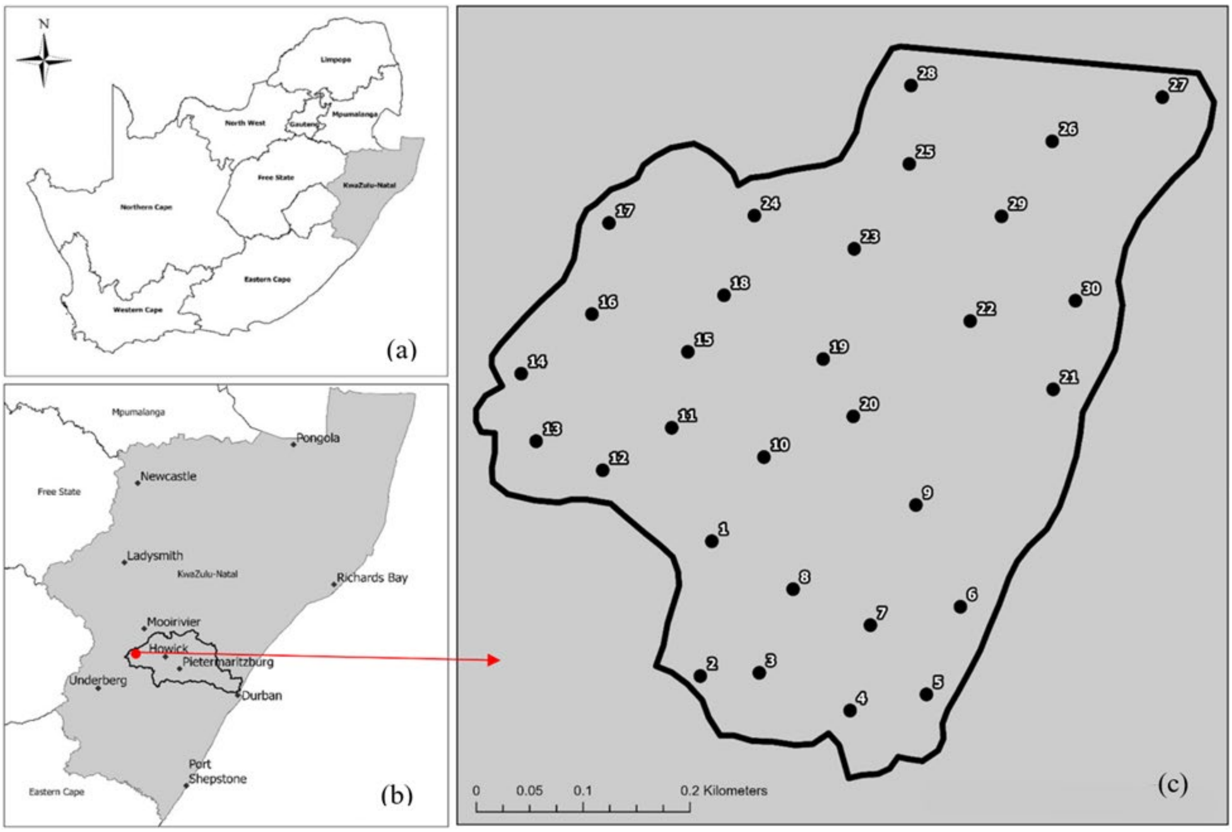
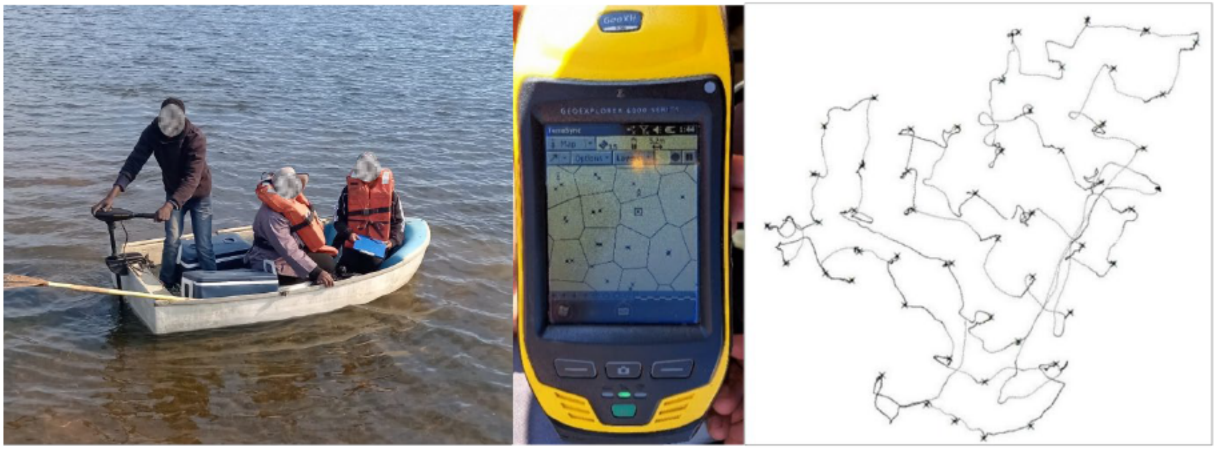


Figure 3.1 (a) KwaZulu Natal highlighted within South Africa, (b) The uMngeni catchment depicted within KwaZulu Natal, highlighting the location of the High Flight farm dam in the upper catchment, (c) The High Flight Farm dam along with 30 sampling point locations.

3.2.2 Field data collection, sampling and surveying of surface water temperature, TSS and CDOM

Field data measurements were collected once a month in April, June and July 2024. Across the dam, 30 sample points were randomly identified (Figure 3.1), and with the aid of a motorised boat and a Trimble GeoExplorer 6000 series handheld GPS device (typical horizontal accuracy ranging from 0.5 to 1.0 meters), sample coordinates were located (Figure 3.2). At each sample point, the “grab sampling” method was used (Song et al., 2017, Veronez et al., 2018). Furthermore, one litre of water samples were collected 0-50cm below the water’s surface in standard HDPE plastic bottles and stored in a cooler box for lab analysis of TSS and CDOM (Morgan, 2020). Alternately, a multiprobe was utilised to measure the surface water temperature, pH and electrical conductivity at each point, and these measurements were recorded.



(a) (b) (c)

Figure 3.2 (a) Motorised boat used for sample collection, (b) GPS device with pre-loaded sample point co-ordinates, (c) path taken across the dam following the GPS device

3.2.3 Laboratory analysis of data

In the laboratory, the APHA standard method for measuring TSS was followed, whereby 200ml of the sample water from each sample point was measured out into a beaker (APHA, 2005). The individual samples were filtered through 0.45μm pore-sized glass fibre filtration paper inside a vacuum filtration unit. Thereafter, the filter paper, along with its remaining residue, was put into metal dishes (Figure 3.3) and dried in an oven at 104°C for 24 hours. The filter paper was then weighed to calculate the weight of the residue (suspended solids), which was then used to calculate the concentration of TSS using Equation 3.1:

$$\boldsymbol{TSS\ (mg.L)} = \frac{\boldsymbol{(Weight\ of\ filter + dried\ residue) - (Weight\ of\ filter) \times 1000}}{\boldsymbol{200}}$$

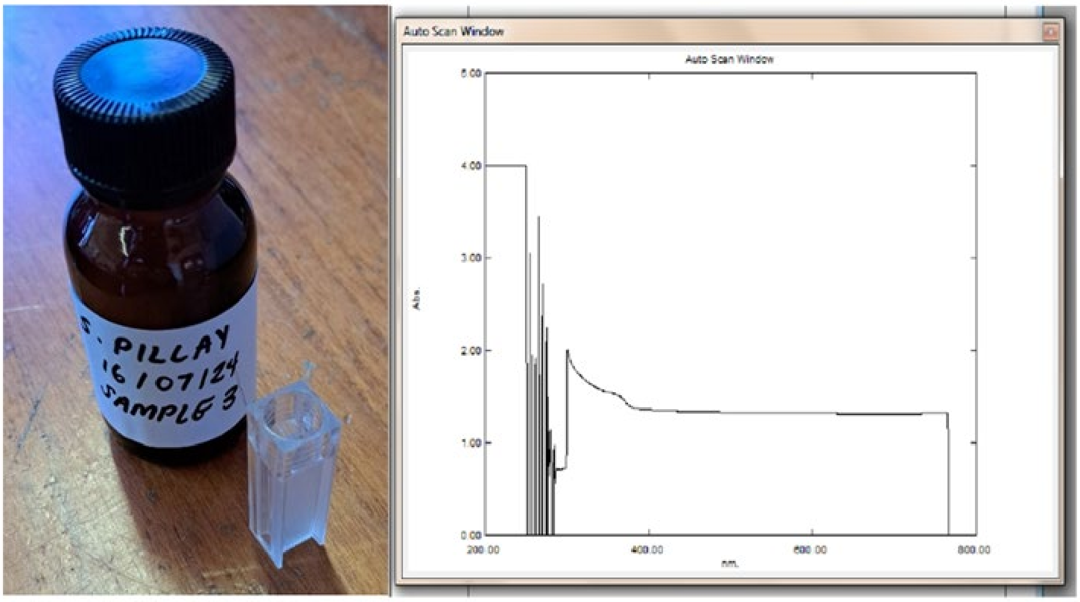
Equation 3.1 Concentration of TSS calculated from the weight of dried residue extracted from 200ml of the water samples.

(a) (b)

Figure 3.3 (a) Vacuum filtration unit containing a glass fibre filtration paper, (b) filter paper along with the filtered residue.

Thereafter, the remaining filtrate which passed through the glass fibre filtration unit was placed in 50ml glass amber bottles to minimise light exposure (Figure 3.4a) and refrigerated for further analysis of CDOM concentration using a spectrophotometer to measure the absorption of light at specific wavelengths (Röttgers13 et al.). The first step in determining CDOM absorption was to calibrate the spectrophotometer with quinine sulfate as a standard method for creating a calibration curve to quantify CDOM concentrations (Coble, 1996). Quinine sulfate, a widely used fluorescing compound, was used to investigate the best wavelength for fluorescence excitation. Approximately 100mg of quinine sulphate was dissolved in 100 ml of a 0.1 N sulfuric acid solution to prepare a stock solution and working standards. A series of quinine sulfate solutions with concentrations of 0.5, 1.0, 1.5, 2.0, and 2.5 µg/mL were prepared by serial dilution of the stock solution to produce the calibration curve.

The fluorescence intensity of each standard was measured using a spectrophotometer at an excitation wavelength range of 200 nm to 800 nm (Figure 3.4b).



(a) (b)

Figure 3.4 (a) 50ml glass amber bottles containing filtrate, (b) wavelength range from 200nm to 800nm indicating fluorescence excitation

The measured fluorescence values were plotted against the known concentrations of quinine sulfate to produce a linear calibration curve (Figure 3.5), expressed as $y=mx+b$, where y represents the absorbance or fluorescence intensity, x is the concentration, m is the slope, and b is the intercept. This approach was chosen based on its simplicity, reproducibility and based on the theoretical foundation of the Beer–Lambert law, which predicts a linear relationship between concentration and absorbance under ideal conditions, particularly for dilute solutions (Gobrecht et al., 2015). Once the calibration curve was established, the filtered water samples were prepared in individual 1ml cuvettes and the absorbance of each sample was measured under the same conditions as the standards. Finally, using the calibration curve equation, the samples' absorbance values were interpolated to determine their CDOM concentrations expressed in mg/L (Zeng et al., 2023).

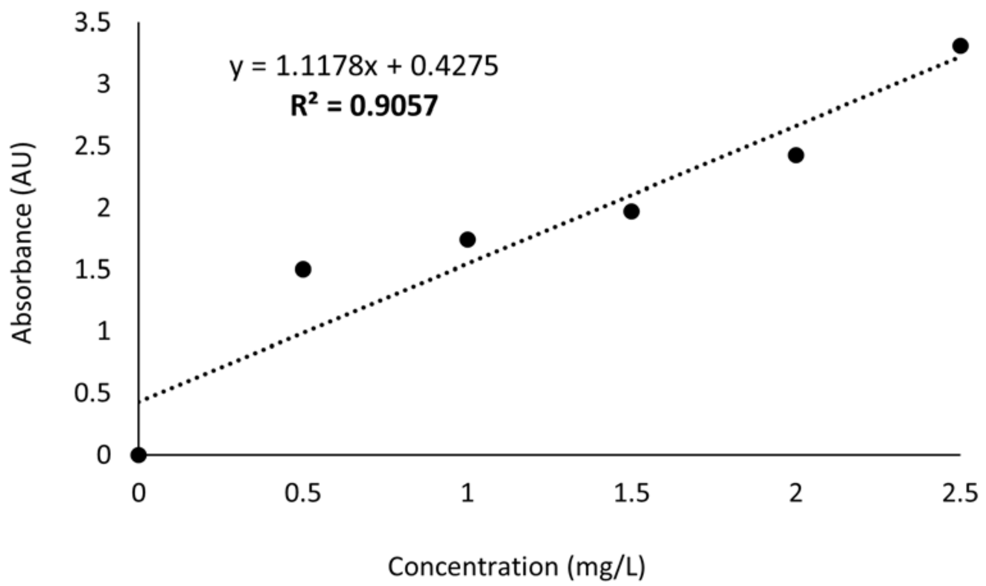


Figure 3.5 Calibration curve of a quinine sulphate standard stock solution

3.2.4 UAV-derived data collection

3.2.4.1 DJI Matric 300 and MicaSense Altum

For aerial-based flights over the High Flight farm dam, the DJI Matrice 300 (DJI M-300) platform mounted with a MicaSense Altum camera and Downwelling Light Sensor 2 (DLS-2) was used. The DJI M-300 is a rotary-wing drone which has vertical take-off and landing (VTOL) technology, making it suitable for small-scale imaging (Figure 3.6). The DJI M-300 platform`s specifications include its 15 km transmission range, a maximum altitude of 7000 m, obstacle avoidance, flightpath planning and locational position tracker (DJI, 2023). Furthermore, the drone can be flown for a maximum flight time of 55 minutes (without payload), and can reach a maximum speed of 27 m/s, outperforming most drone platforms on the market (DJI, 2023). Moreover, the MicaSense Altum camera is a multispectral and thermal imaging sensor that integrates five spectral high-resolution narrow bands: blue, green, red, red-edge and near-infrared with a radiometric longwave infrared thermal camera (Table 3.1) (Morgan, 2020). The high-performance camera offers synchronised multispectral and thermal image capture and uses a global shutter of up to a one-second capture rate for precise and aligned imagery (Hutton et al., 2020).

(a) (b) (c)

Figure 3.6 (a) MicaSense Altum multispectral camera, (b) DJI Matrice 300 (DJI M-300) platform mounted with a MicaSense Altum camera, (c) DJI M-300 used for aerial-based flights over the High Flight farm dam

Table 3.1 Spectral band characteristics of the MicaSense Altum imaging sensor

Band	Spectral colour	Band centre/range
1	Blue	475nm
2	Green	560nm
3	Red	668nm
4	Red-edge	717nm
5	Near-infrared	841nm
6	Thermal	8000-14 000nm

3.2.4.2 Image acquisition and processing

Before the DJI Matrice 300 (M-300) drone was flown over the High Flight farm dam, a shapefile of the dam was created in Google Earth Pro and imported into the DJI M-300 smart console. This was then used to design a flight plan covering the dam. The flight plan enabled a hands-free drone flight mission over the dam. Additional flight planning was performed to determine the best-suited flight path, flight time, flight altitude, energy consumption and battery conditions of the drone (Figure 3.7a).

Before and after the flight, the drone was calibrated using the MicaSense Altum calibrated reflectance panel (CRP). This comprised of the user manually taking an image directly over the CRP, while ensuring that the image is unshaded, in order to discern the lighting conditions of the specific flight date, time, and location (Figure 3.7b). Simultaneously, in-situ measurements of temperature, TSS, and CDOM were collected across the dam, and remotely sensed data was collected whereby the drone was flown at an altitude of 100m across the reservoir. Drone flights were conducted once a month in April, June and July 2024 on days with clear skies and minimal wind conditions. Furthermore, the study adhered to the regulations set out by the South African Civil Aviation Authority (SACAA) under Part 101, which governs the use of remotely piloted aircraft systems (RPAS). All drone flights were conducted by trained personnel, operated within visual line of sight and confined to agricultural land with explicit permission from the landowner (South African Civil Aviation Authority, 2015).


(a) (b)

Figure 3.7 (a) UAV Flight plan imported into the DJI M-300 smart console, (b) UAV calibration using the MicaSense Altum calibrated reflectance panel (CRP)

Once the drone had been flown and multispectral images were generated, Pix4Dfields software was used to mosaic and radiometrically correct the images. The Pix4D software utilised weighted averages of pixels in the original images that correspond to each individual pixel and provided greater weight to the images where the pixels were more central in order to calculate the reflectance values of pixels in the processed orthomosaics (Olivetti et al., 2020). The value of each pixel is influenced by a number of variables, such as scene circumstances, sensor settings, and sensor characteristics. Finally, radiometric corrections were applied to enhance the quality of data, irradiance and sun angle parameters for clear and overcast skies (Olivetti et al., 2020, Cillero Castro et al., 2020). Once processed, a final orthomosaic and a digital elevation model (DEM) GeoTIFF images were generated. The orthomosaic was georeferenced in ArcGIS Pro 3.3 with the use of ground reference points generated from Google Earth Pro and referenced to the Universal Transverse Mercator (UTM zone 36S) projection. Additionally, the thermal infrared band was converted to absolute temperature values in ArcGIS Pro using Equation 3.2:

$$\boldsymbol{Temperature\ (°C) = \frac{Thermal\ infrared\ (Band\ 6)}{100} - 273.15}$$

Equation 3.2 Thermal band six conversions to absolute temperature (°C)

3.2.5 Spectral indices for estimating and predicting TSS and CDOM

To further explain the methodologies utilised in estimating and predicting TSS and CDOM concentrations, Figure 3.8 can be used.

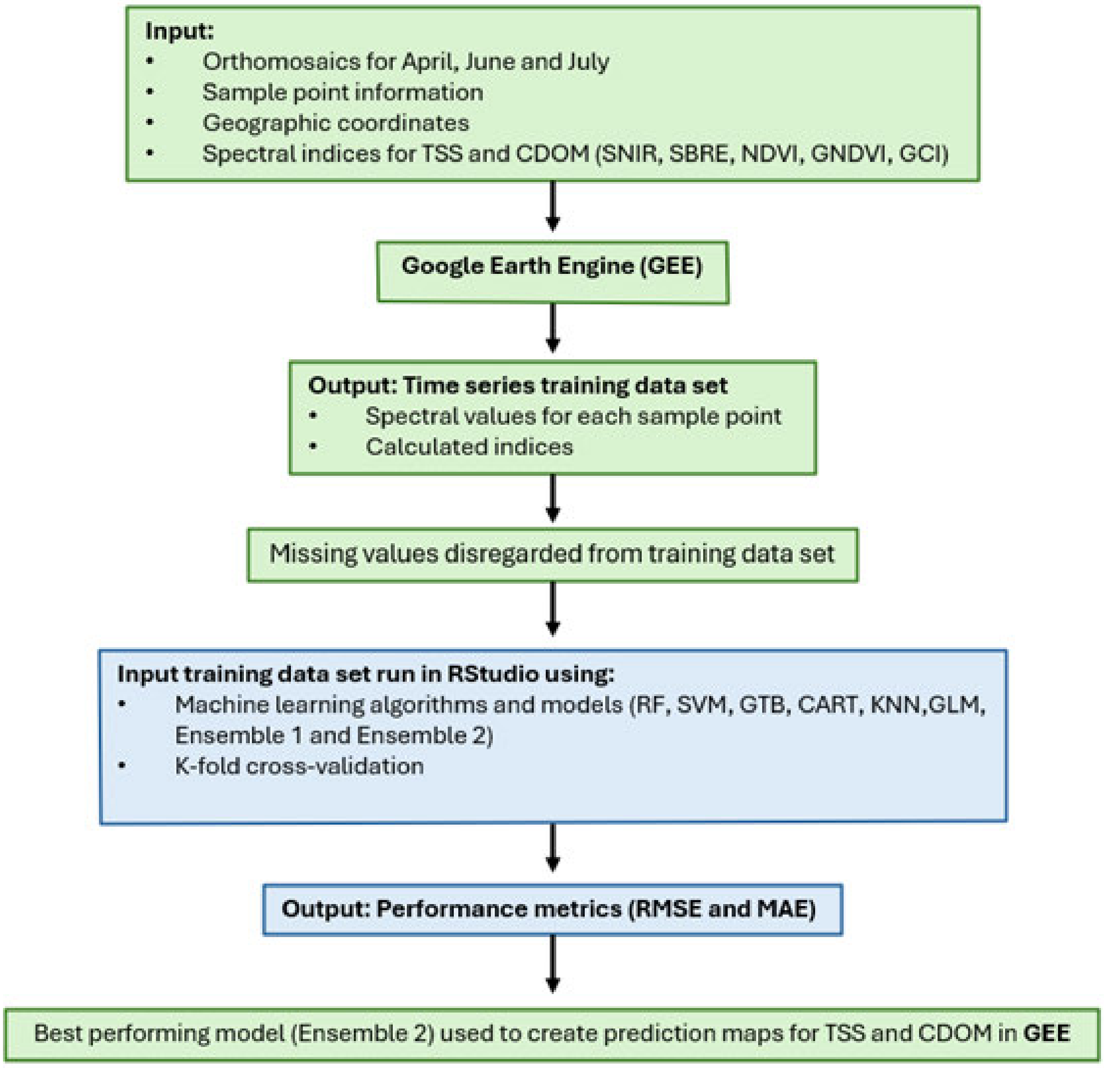


Figure 3.8 Methodology used in estimating and predicting TSS and CDOM concentrations

To analyse TSS and CDOM, the methodology involved leveraging Google Earth Engine (GEE) to process the orthomosaics for April, June and July. The five spectral bands captured in the orthomosaics were uploaded to GEE, along with the corresponding sample point information, including point numbers, geographic coordinates and relevant spectral indices used to quantify TSS and CDOM concentrations. Spectral indices for TSS are typically derived from wavelengths from the red and near-infrared portions of the electromagnetic spectrum due to suspended particles reflecting scattered light (Pillay et al., 2024). For this reason, the Specific Near-Infrared Index (SNIR) and the Shortwave Band Reflectance Edge index (SBRE) were chosen. Additionally, spectral indices for CDOM are derived from wavelengths in the visible and ultraviolet portions of the electromagnetic spectrum since those bands are sensitive to changes in photosynthetic activity linked to organic material in water (Rahul, 2023, Larson, 2018). Therefore, the Normalized Difference Vegetation Index (NDVI), Green Normalized Difference Vegetation Index (GNDVI) and Green Chlorophyll Index (GCI) were chosen (Table 3.2).

Table 3.2 Spectral indices used to characterise TSS and CDOM

Water Quality parameter	Spectral index	Abbreviation	Formula	Author and year
TSS	Specific Near-Infrared Index	SNIR	$SNIR = \frac{NIR - Red}{NIR + Red}$	Adjovu et al. (2023)
	Shortwave Band Reflectance Edge	SBRE	$SBRE = \frac{SWIR - NIR}{SWIR + NIR}$	Knaeps et al. (2015)
CDOM	Normalized Difference Vegetation Index	NDVI	$NDVI = \frac{NIR - Red}{NIR + Red}$	Adjovu (2023) Viso-Vázquez (2021)
	Green Normalized Difference Vegetation Index	GNDVI	$GNDVI = \frac{NIR - Green}{NIR + Green}$	Yépez (2024) Viso-Vázquez (2021)
	Green Chlorophyll Index	GCI	$GCI = \frac{NIR}{Green} - 1$	Yépez (2024)

Using a custom GEE script, the uploaded data was processed to extract the values of each band and calculated indices for the sample points. After numerous test runs, it was determined that only a portion of the orthomosaic could be used in GEE instead of the entire map due to computational constraints and data limitations (Figure 3.9). Processing the entire orthomosaic resulted in errors and crashes in GEE, likely due to the high resolution and large file size of the dataset, which exceeded the processing capabilities. Additionally, since the number of data points was very low, focusing on a smaller, relevant section of the orthomosaic ensured that the calculations for indices were accurate and computationally feasible while aligning with the spatial coverage of the sample points. This targeted approach optimized performance and prevented system overloads.

Figure 3.9 Portion of the orthomosaics used in GEE due to computational constraints and data limitations

After processing in Google Earth Engine, a time series training dataset was generated in the form of a CSV file. This dataset included spectral values for each sample point over time, along with the calculated indices. However, the dataset contained missing values, likely due to incomplete data collection or gaps in the processing of certain points. These missing data entries were disregarded, ensuring the analysis focused on valid and consistent measurements of the spectral indices and their relationship to TSS and CDOM.

In RStudio software version 2024.09.0, several packages were loaded to facilitate the processing of raster data and the analysis of the time series training dataset. These packages provided the tools to handle spatial data, perform statistical analyses and implement machine learning algorithms. The time series training dataset, containing spectral values and indices was uploaded to RStudio for model development. Using this data and a custom script, various machine learning models were run, including algorithms such as Random Forest (RF), Support Vector Machines (SVM), Gradient Boosting Trees (GBT), Classification and Regression Trees (CART), k-Nearest Neighbours (k-NN), and Generalized Linear Models (GLM). These models were selected based on the findings of the systematic literature review presented in Chapter 2. Furthermore, to ensure model robustness and prevent overfitting, a K-fold Cross-Validation approach was implemented, along with a 70/30 train-test data split. These techniques allowed each model to be tested across different subsets of the data, enhancing reliability and accuracy. Model performance was recorded using standard accuracy metrics and cross-validation statistics.

To further enhance the robustness and predictive accuracy of the model outputs, model ensembles were created by combining the best attributes from the individual models (Xiao, 2022, Wu and Levinson, 2022). Ensemble 1 combined the predictions from Random Forest, SVM and Gradient Boosting Trees using a simple averaging (mean) method. This approach assumed that averaging the outputs of high-performing models would reduce variance and improve generalisation. Ensemble 2 included a broader combination, utilising RF, SVM, GBT and CART, also utilising simple averaging and this ensemble was created to assess whether the inclusion of additional models further improved prediction performance. The performance results for the model ensembles were also recorded, providing a more robust and reliable set of predictions for TSS and CDOM estimation. Finally, once the model ensembles were run and the performance metrics were recorded, Google Earth Engine created prediction maps for TSS and CDOM. The ensemble models produced higher accuracies and were applied using the spectral indices and band data as inputs. Google Earth Engine's computational power aided in generating prediction maps for both TSS and CDOM. These maps visually represented the estimated concentrations of TSS and CDOM, providing valuable insights into the distribution of these water quality parameters.

3.2.6 Evaluation of spectral indices and machine learning algorithms

Accuracy assessments were conducted to assess model performance for the predicted TSS and CDOM concentrations. The accuracy metrics used were the root-mean-squared error (RMSE) and the Mean absolute error (MAE). The RMSE assessed the error magnitude between the field measurements and modelled outputs of TSS and CDOM (Equation 3.3a). In contrast, the MAE measured the average absolute differences between the predicted values and the field measurements for TSS and CDOM (Equation 3.3b).

(a) $RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$

(b) $MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|$

Where:

n = the number of data points

y_i = the actual value for the i-th data point

$\hat{y}_i$ = the predicted value for the i-th data point

$(y_i - \hat{y}_i)^2$ = the square difference between the actual and predicted values for each data point

$|y_i - \hat{y}_i|$ = the absolute difference between the actual and predicted values for each data point

Equation 3.3 (a) equation used to calculate RMSE, (b) equation used to calculate MAE

These metrics were calculated for each individual model as well as the ensemble models, providing a comparative basis for assessing which modelling approaches resulted in the most reliable predictions. While Google Earth Engines platform limitations prevented the generation of visual loss curves, the use of K-fold cross-validation, training and testing datasets and multiple accuracy metrics provided sufficient means of evaluating and mitigating potential model overfitting. This comprehensive evaluation approach ensured that machine learning models used in this study were both appropriate and reliable for addressing the research objectives.

3.3 Results

3.3.1 Temperature

Figure 3.10 below shows the water temperature results, indicating the fluctuations from April, June and July, as well as across the dam from the inlet (Point 1) to the outlet (Point 30). The solid line depicts the measurements using the multiprobe, while the dotted line depicts the measurements collected by the UAV. When looking at the differences between multiprobe and UAV data, it is evident that in April, the UAV recorded higher temperature values ranging from 15-21 °C, while the multiprobe recorded values ranging from 17-19 °C. In June and July, however, the UAV recorded values were lower than those recorded by the multiprobe, indicating a consistent offset between the two methods. When looking at seasonal variation, it is evident that water temperatures decrease from April to July, signifying seasonal change from Autumn to Winter. In April, temperatures were between 15 °C and 21 °C for both multiprobe and UAV data, while in July, temperatures declined. The recordings were between 7 °C and 14 °C for both methods.

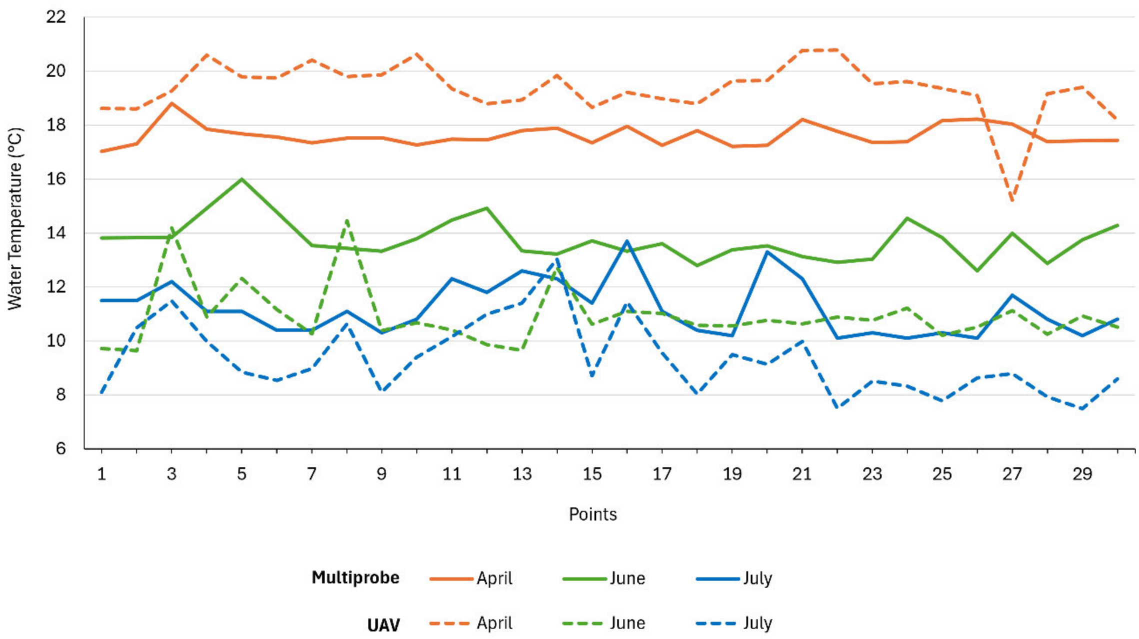


Figure 3.10 Water temperature measured by a multiprobe and UAV

Furthermore, the thermal maps in Figure 3.11 depict UAV-derived water temperature data from across the dam, starting at the inlet and moving to the outlet during April, June, and July. These maps emphasised the spatial and temporal variations, and it can be noted that gaps in the maps are due to missing data that had not been collected by the drone which was caused by intermittent GPS signal loss during drone flights. In April, higher temperatures (up to 22 °C) are observed near the inlet (Points 1-8), with a gradual decrease toward the outlet (Points 26-30). By June, water temperatures drop significantly across the reservoir, ranging from 10 °C to 16 °C, indicating seasonal change. At the inlet and specifically around aquatic vegetation, temperatures are predominantly higher. However, the spatial gradient across the rest of the dam is less distinct, with cooler temperatures observed more uniformly across the area. In July, the overall water temperature decreases further, especially around the aquatic vegetation, with temperatures ranging from 15 °C to 17°C. Warmer zones are still concentrated near the inlet, while the outlet region shows the coolest temperatures, suggesting reduced thermal inputs and increased mixing across the dam during the cooler months. This seasonal trend highlights the influence of inflow dynamics and environmental cooling on water temperature distribution within the dam.

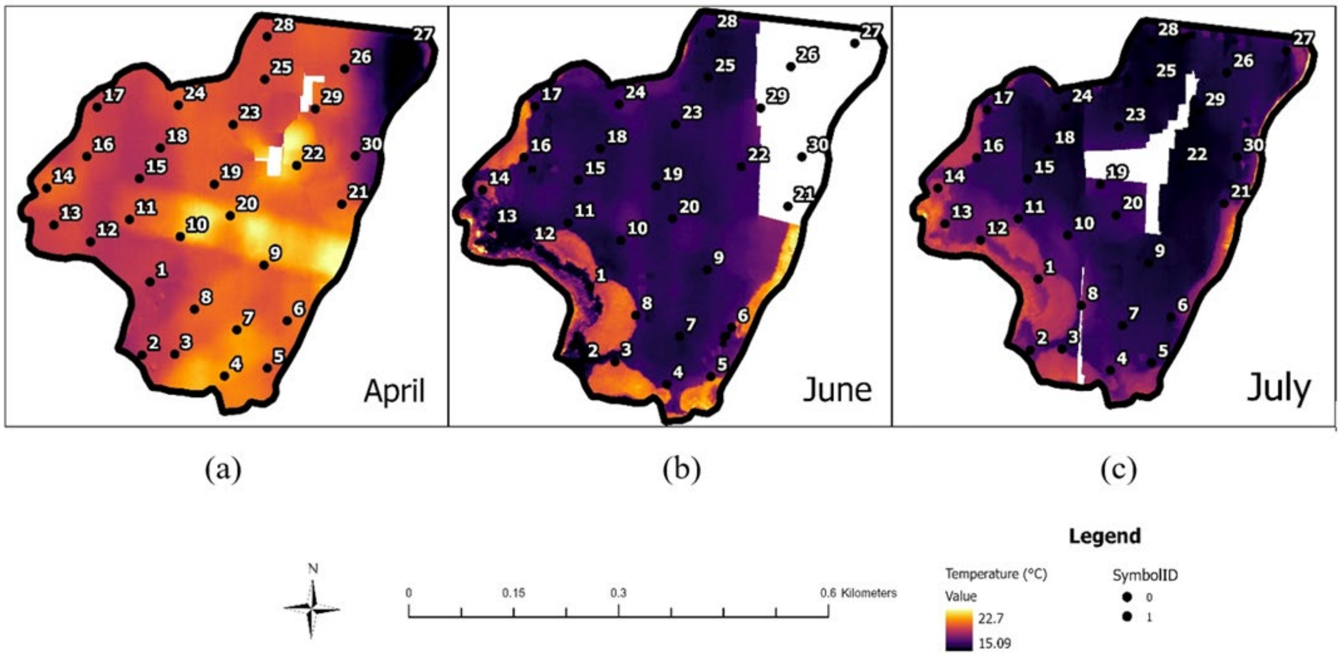


Figure 3.11 Spatial and temporal variations of surface water temperature for April (a), June (b) and July (c).

Table 3.3 provides insight into the mean and median water temperatures for April, June and July, which were collected by the multiprobe and UAV. Drawing from Table 3.3, it is evident that mean water temperatures collected by both methods decreased from April to July. Values collected by the multiprobe decreased from 17.62 °C in April to 13.70 °C in June and further to 11.40 °C in July. At the same time, values collected by the UAV decreased from 19.34 °C in April to 10.93 °C in June and further to 9.33 °C in July. This further emphasises the temporal variations in surface water temperature from Autumn to Winter. Similarly, median values for both the multiprobe and the UAV display a decreasing trend of water temperatures from April to July.

Table 3.3 Mean and median water temperatures for April, June and July, collected by the multiprobe and UAV

	Temperature (°C)	April	June	July
Multiprobe	Mean	17.62	13.70	11.40

	Median	17.50	13.46	11.10
UAV	Mean	19.34	10.93	9.33
	Median	19.38	10.65	8.91

3.3.2 Total Suspended Solids (TSS)

Figure 3.12 illustrates the TSS concentrations measured from the water samples from April to July across sampling points from the inlet (Point 1) to the outlet (Point 30). In all months, TSS concentrations are highest at the inlet, where levels peak at approximately 250 mg/L. This indicates substantial sediment and organic matter upstream, mainly due to the surrounding aquatic vegetation in the dam. As the water flows toward the outlet, TSS concentrations decrease sharply, stabilizing below 100 mg/L. In June, TSS levels follow a similar pattern, with concentrations peaking around 200 mg/L at the inlet and decreasing more gradually compared to April. Notable fluctuations are observed between Points 7 and 25. In July, TSS levels at the inlet are comparatively lower and exhibit less variation throughout the reservoir. At the outlet (Point 30), TSS concentrations remain consistently low (<50 mg/L) across all months, highlighting effective sediment deposition within the reservoir. Overall, seasonal trends indicate higher sediment loads in April, likely linked to increased runoff with a progressive decline in sediment distribution by July.

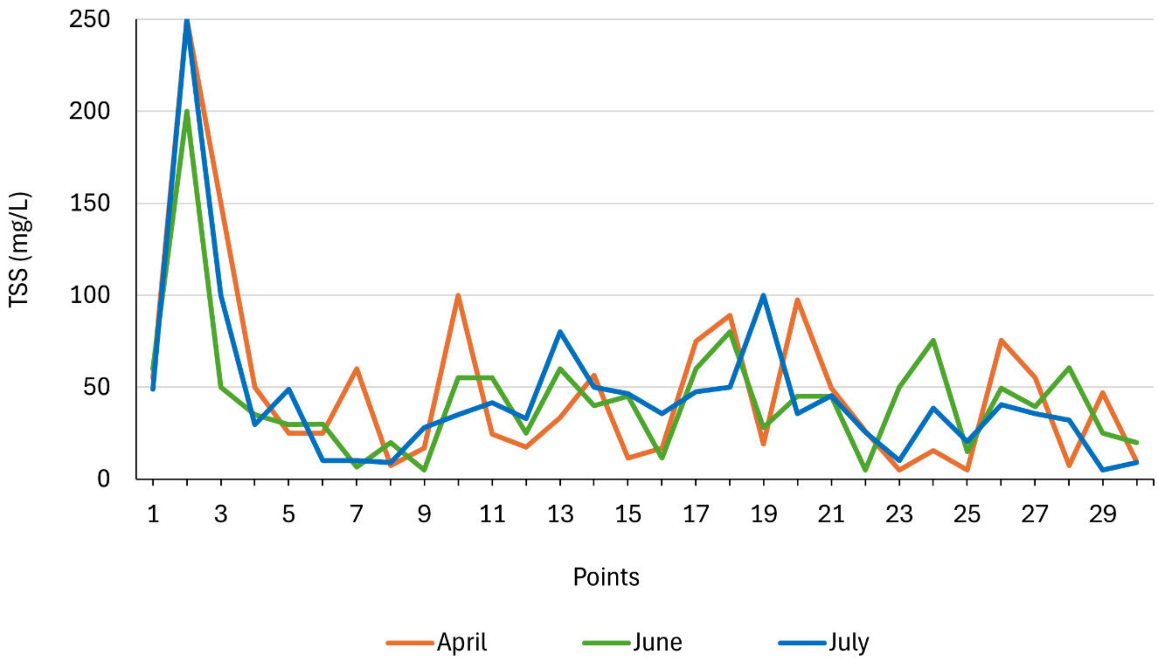


Figure 3.12 TSS concentrations measured using the collected water samples in April, June and July

Subsequently, Table 3.4 shows the mean and median in-situ TSS concentrations for April, June and July. From this, it is evident that the mean values decrease from month to month. From April to June, values decrease from 49.2 to 46.6 mg/L and down to 44.8 mg/L in July, emphasising the influences of seasonal variation on TSS concentrations. Furthermore, the median values differ from the decreasing trend set by the mean values such that in April, the median value is 29.8, in June the value is 44.5 and in July the value is 35.5 mg/L.

Table 3.4 Mean and median in-situ TSS concentrations for April, June and July.

TSS (mg/L)	April	June	July
Mean	49.2	46.6	44.8
Median	29.8	44.5	35.5

Table 3.5 summarizes the performance of various machine learning algorithms used to predict TSS concentrations. Individual models such as the Generalized Linear Model (GLM), k-Nearest Neighbours (k-NN), Classification and Regression Trees (CART), Random Forest (RF), Gradient Tree Boosting (GTB) and Support Vector Machine (SVM) showed RMSE

values ranging from 47.70 to 51.20 mg/L. These models also showed MAE values ranging from 34.00 to 38.40 mg/L. The SVM model exhibited the lowest RMSE of 45.20 mg/L and the lowest MAE of 30.90 mg/L among the individual models. Ensemble models outperformed individual algorithms, demonstrating the advantage of combining multiple approaches. Ensemble 2 achieved the lowest RMSE of 30.50 mg/L and MAE of 19.20 mg/L. This indicates that the ensemble approach moderately captured the complex relationships in the data, leading to fewer errors and more reliable TSS predictions compared to standalone models.

Table 3.5 Performance metrics for individual algorithms and model ensembles for predicting TSS concentrations

	TSS	
Model	**RMSE (mg/L)**	**MAE (mg/L)**
GLM	51.20	38.40
k-NN	48.00	34.50
CART	47.70	34.00
RF	48.60	35.60
GTB	50.50	37.00
SVM	45.20	30.90
Ensemble 1	45.70	31.80
Ensemble 2	30.50	19.20

Furthermore, Figure 3.13 below illustrates the observed spatial distribution of TSS concentrations for April, June and July. When looking at the observed maps it is evident that across all the months, higher TSS concentrations were evident within the aquatic vegetation blooms. In April, higher TSS concentrations were observed near the inlet areas, likely due to increased runoff carrying sediments into the reservoir during this period. By June, the TSS levels are slightly lower, indicating reduced sediment inputs or the settling of particulates during winter months. In July, there was an increase in TSS concentrations within the aquatic vegetation. Additionally, higher TSS concentrations can be noted within the water.

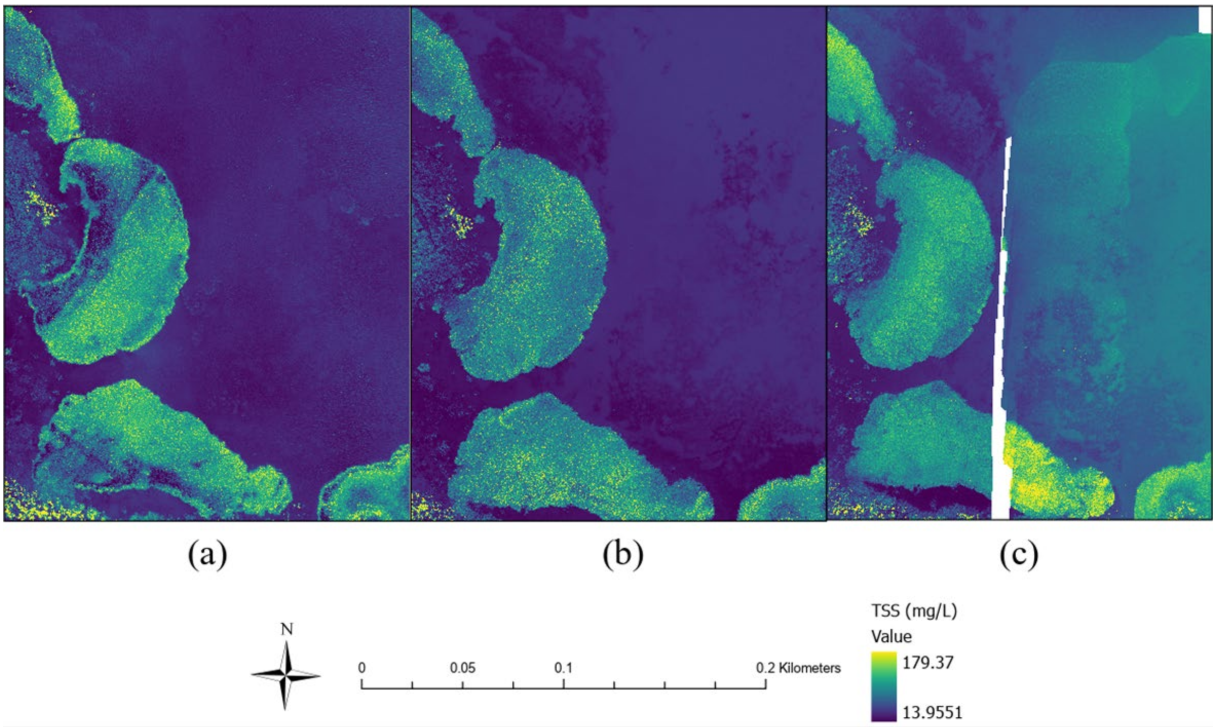


Figure 3.13 Observed spatial distribution of TSS concentrations for April (a), June (b), and July (c).

Figure 3.14 depicts the predicted spatial distribution of TSS concentrations for April, June and July, created using the ensemble 2 model, which achieved the lowest RMSE value of 30.50 mg/L and MAE value of 19.20 mg/L. This indicates fewer errors between the observed and predicted TSS compared to other models, suggesting that the ensemble effectively captured the spatial and temporal variations.

In April, the predicted TSS concentrations show higher values, predominantly near the inlet regions and surrounding the aquatic vegetation, reflecting elevated sediment inflows likely due to increased runoff. By June, a noticeable decline in TSS levels is observed across much of the area, with more uniform and lower concentrations of TSS, indicating reduced sediment inputs during the drier period. In July, TSS levels increase slightly in certain regions, possibly due to changes in hydrological systems during this period.

It can also be noted from Figure 3.14 that the predicted maps for TSS concentrations appear fuzzy or blurred due to the nature of the modelling and interpolation processes used in generating them. Machine learning models, such as the model ensemble used in this study, predict values based on input variables like spectral indices, which may not capture fine spatial details. The fuzziness arises due to the model's generalised patterns from the training data, smoothing and oversimplifying spatial variations in TSS.

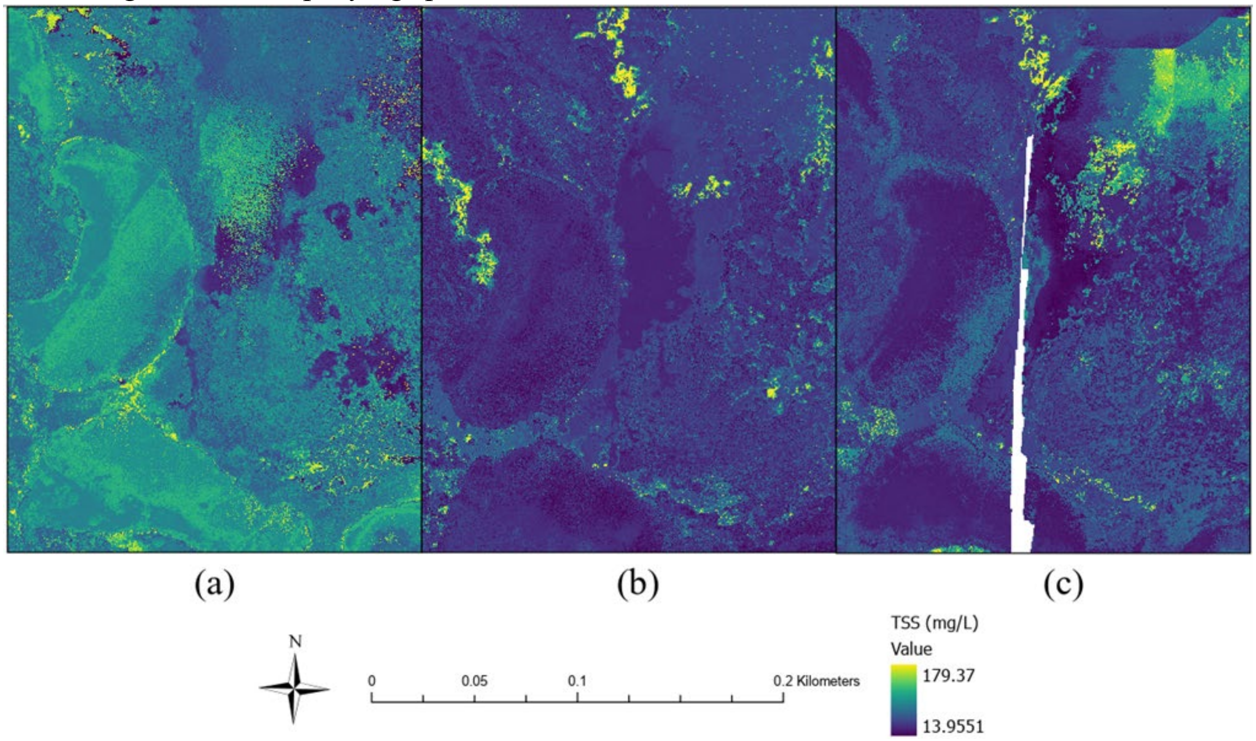


Figure 3.14 Predicted maps showing the spatial variability of TSS concentrations for April (a), June (b) and July (c)

3.3.3 Chromophoric Dissolved Organic Matter (CDOM)

When looking at CDOM, Figure 3.15 illustrates the concentrations across 30 points, ranging from the inlet at point 1 to the outlet at point 30 during April, June and July. A distinct seasonal variation in CDOM levels is evident, with April exhibiting the highest concentrations overall. Around the inlet (from points 1-5), April CDOM levels start at approximately 1.5 mg/L, significantly higher than June and July. From the inlet to the outlet, a general declining trend in CDOM is observed across all months. However, the decline is not uniform and pronounced fluctuations are evident. April shows the greatest variability with peaks near points 9, 15, 22 and 26, reflecting influences such as inflow from tributaries or variations in organic matter input. In contrast, June and July show lower concentrations and less pronounced peaks. Notably, July exhibits more stable trends, except for a peak at point 9. Closer to the outlet (point 27-30), CDOM concentrations decrease below 1 mg/L for all months. The results highlight spatial and seasonal variations, with higher CDOM concentrations in April potentially linked to runoff or increased organic matter.

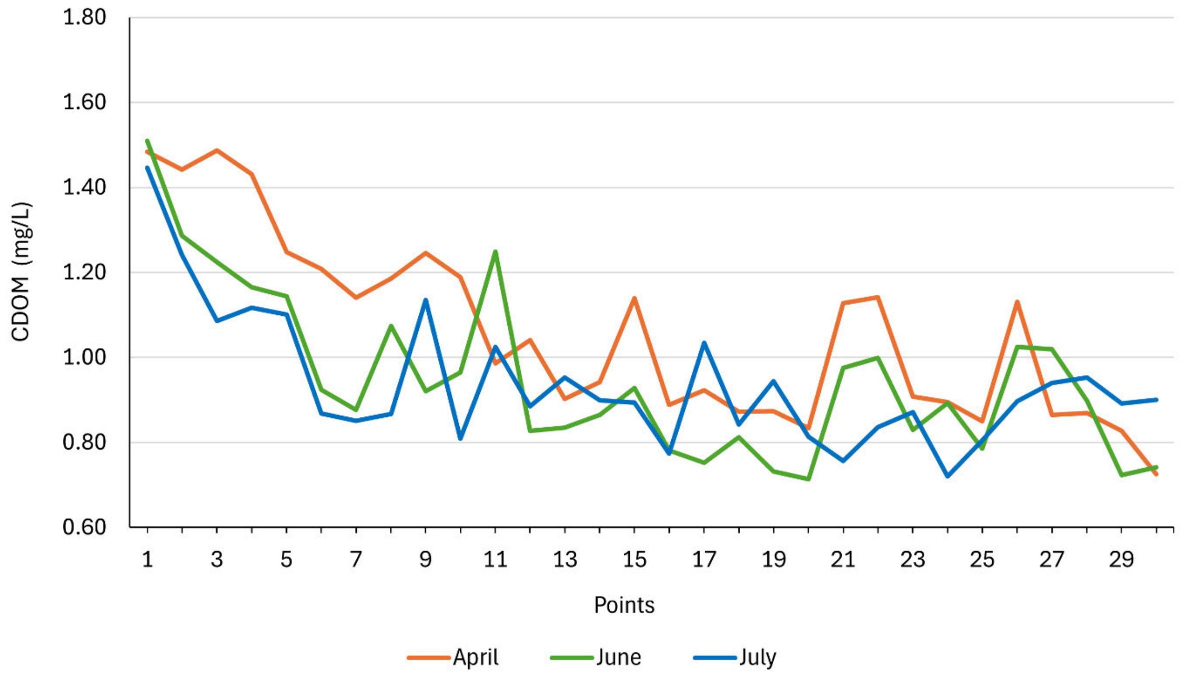


Figure 3.15 In-situ CDOM concentrations in April, June and July

Table 3.6 shows the mean and median in-situ CDOM concentrations for April, June and July. From this, it is evident that June has the highest mean value of 1.003 mg/L and the highest median value of 0.960 mg/L compared to April and July. Furthermore, April has the lowest mean and median values of 0.804 and 0.705 mg/L.

Table 3.6 Mean and median in-situ CDOM concentrations for April, June and July

CDOM (mg/L)	April	June	July
Mean	0.804	1.003	0.966
Median	0.705	0.960	0.899

Table 3.7 summarizes the performance of various machine learning models in predicting CDOM concentrations evaluated using RMSE and MAE. Individual models such as the Generalized Linear Model (GLM), k-Nearest Neighbours (k-NN), Classification and Regression Trees (CART), Random Forest (RF), Gradient Tree Boosting (GTB) and Support Vector Machine (SVM) showed RMSE values ranging from 0.26 to 0.28 mg/L. These models also showed MAE values ranging from 0.21 to 0.23 mg/L. Among the machine learning

algorithms, Support Vector Machines (SVM) achieved the best performance, with the lowest RMSE of 0.25 mg/L and the lowest MAE of 0.20 mg/L.

However, model ensembles significantly outperformed the individual algorithms. Ensemble 2 demonstrated the highest predictive accuracy with an RMSE value of 0.17 mg/L and an MAE value of 0.12 mg/L, indicating a strong ability to explain the variability in CDOM concentrations. In comparison, Ensemble 1 performed less effectively, with RMSE and MAE values of 0.25 and 0.20 mg/l, matching SVM. This highlights the effectiveness of combining multiple algorithms in Ensemble 2, which leveraged the strengths of different models to reduce prediction errors and improve overall reliability.

Table 3.7 Performance metrics for individual algorithms and model ensembles for predicting CDOM concentrations

CDOM		
Model	**RMSE (mg/L)**	**MAE (mg/L)**
GLM	0.28	0.23
k-NN	0.26	0.21
CART	0.27	0.21
RF	0.26	0.21
GTB	0.26	0.21
SVM	0.25	0.20
Ensemble 1	0.25	0.20
Ensemble 2	0.17	0.12

Furthermore, Figure 3.16 below illustrates the observed spatial distribution of CDOM concentrations for April, June and July. In April, higher concentrations of CDOM (represented by darker shades of blue) are evident across the vegetative areas, particularly influenced by runoff and organic matter input. By June, a slight increase in CDOM concentrations was observed around the vegetation. However, lighter blue shades are evident across the water, indicating lower CDOM concentrations. In July, CDOM concentrations across the water increased and showed higher concentrations compared to April and June.

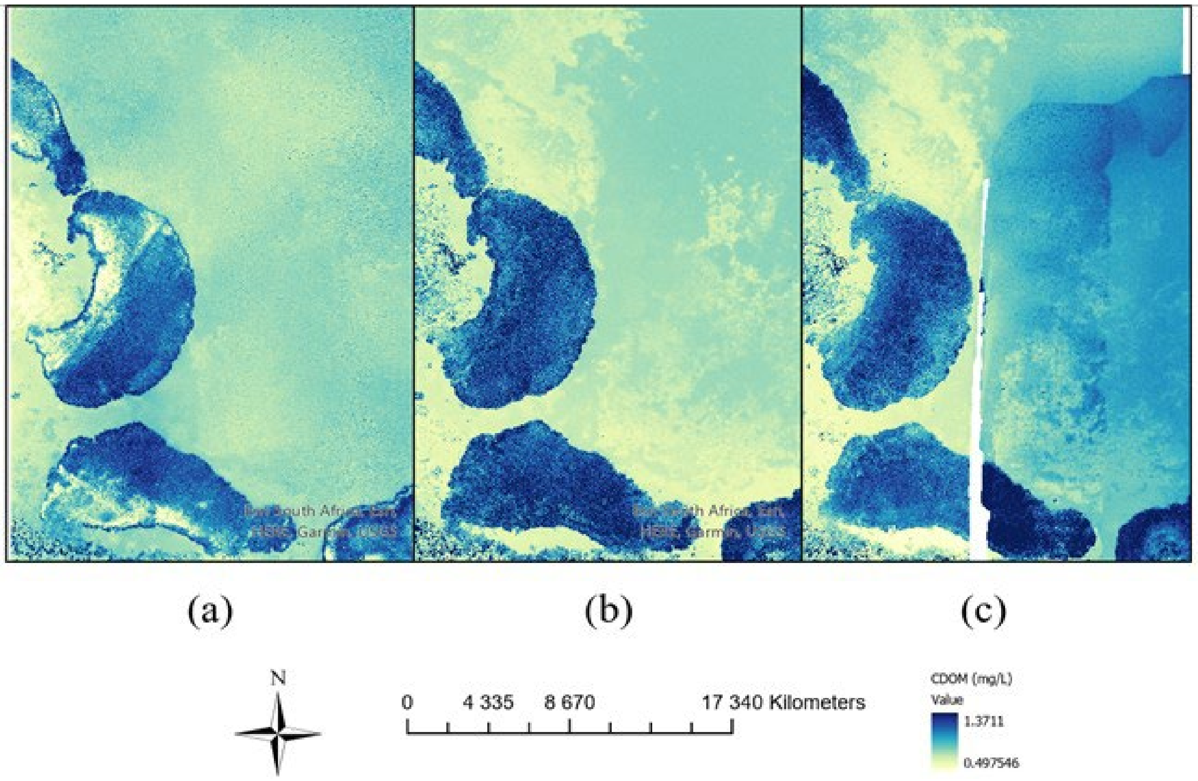


Figure 3.16 Observed spatial distribution of CDOM concentrations for April (a), June (b), and July (c)

Figure 3.17 depicts the predicted spatial distribution of CDOM concentrations for April, June and July, based on model ensemble 2 with an RMSE and MAE of 0.17 and 0.12 mg/L respectively. In April, the predicted map shows higher CDOM concentrations within vegetative areas, consistent with the observed data during this period (Figure 3.16). In June, the predicted CDOM values show an increase in concentrations across the water with a decrease in the vegetative areas. By July, the predicted CDOM values decrease across the water and within the vegetative areas.

While the model adequately predicted CDOM concentrations with low errors, inconsistencies in finer details may still exist due to data not fully captured by the model. Furthermore, it can also be noted in Figure 3.17 that similar to the predicted maps for TSS concentrations, the CDOM maps appear fuzzy or blurred due to the nature of the modelling and interpolation processes used in generating them. Machine learning models, such as the ensemble model used in this study, predict values based on input variables like spectral indices, which may not capture fine spatial details. The fuzziness arises due to the model's generalised patterns from the training data, smoothing and oversimplifying spatial variations in TSS.

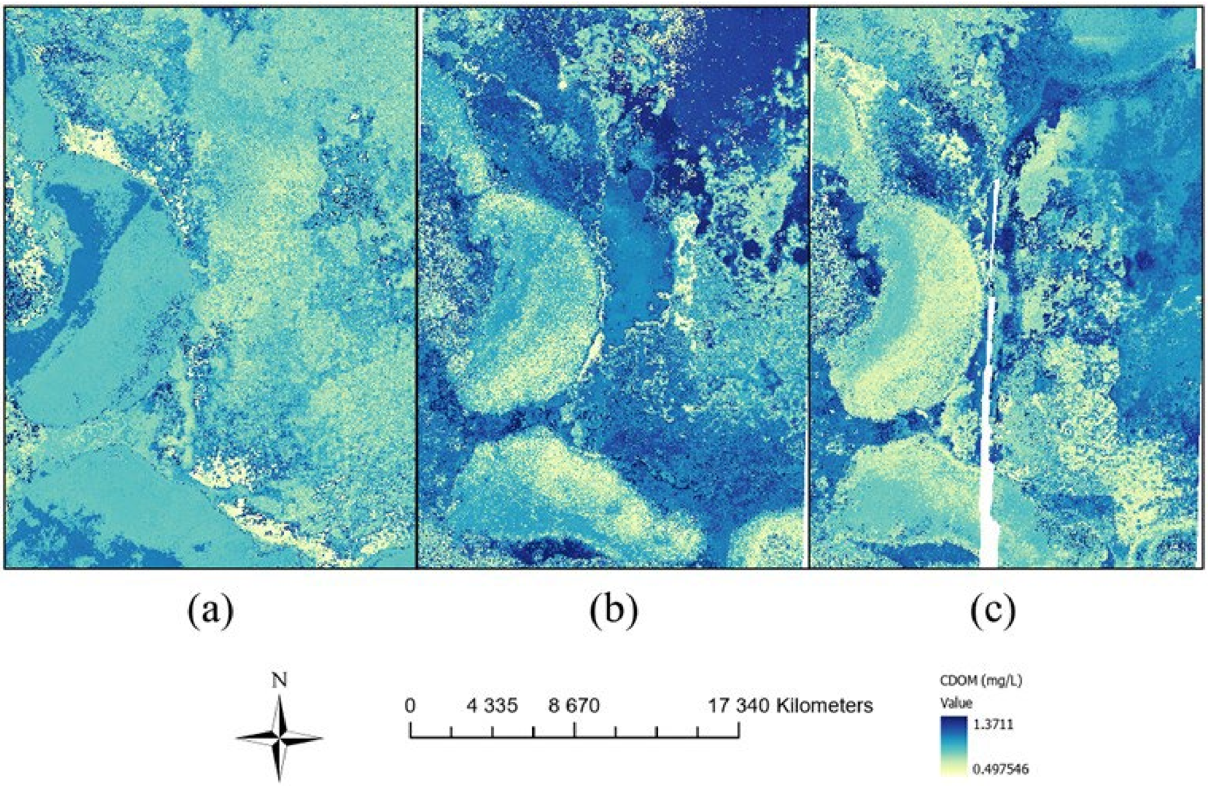


Figure 3.17 Predicted maps showing the spatial variability of CDOM concentrations for April (a), June (b) and July (c).

3.4 Discussion

3.4.1 Synthesis of results

The analysis of temperature in the study revealed its critical role in aquatic ecosystems, particularly under the influence of South Africa's semi-arid climatic conditions. Water temperature in the dam was primarily driven by seasonal variations, solar radiation and atmospheric conditions, with higher temperatures observed during warmer months such as April. Additionally, studies such as Mishra (2017) and Topp (2020) have demonstrated that temperature influences the optical properties of water, which directly impacts the remote sensing of both TSS and CDOM. This was evident when looking at Figure 3.11, Figure 3.13 and Figure 3.16. The observed maps for TSS and CDOM imitate those of temperature such that vegetative zones with higher temperatures displayed higher TSS and CDOM concentrations.

Furthermore, the strong correlations between temperature, TSS and CDOM signifies the importance of understanding thermal dynamics in aquatic systems. For instance, higher temperatures accelerate the breakdown of aquatic vegetation, contributing to increased CDOM, while simultaneously reducing TSS levels by promoting sediment settling (Wang, 2021). Conversely, TSS levels are greatly influenced by runoff events, soil erosion and human activities such as agricultural practices. Rainfall in warmer months significantly contributes to increased TSS due to sediment transport from catchment areas, whereas reduced runoff in drier months results in lower TSS levels (Xu, 2021b). CDOM concentrations, on the other hand, are linked to organic matter decomposition influenced by vegetation cover, land use and river inflows. When looking at the High Flight farm dam, aquatic vegetation played a dual role since it contributed to increased CDOM concentrations through decomposition and influenced light attenuation, which affected the detectability of CDOM concentrations.

The model evaluation results for estimating Total Suspended Solids (TSS) reveal significant variability in performance across algorithms. Among individual models, Support Vector Machines (SVM) performed relatively well, with an RMSE of 45.20 and MAE of 30.90 mg/L. However, most models, including Generalized Linear Models (GLM), k-Nearest Neighbours (k-NN), Classification and Regression Trees (CART), Random Forests (RF) and Gradient Tree Boosting (GTB), yielded higher RMSE and MAE values, indicating more errors within the models. Ensemble models demonstrated higher potential, particularly Ensemble 2, which achieved the best performance with an RMSE of 30.50 and MAE of 19.20 mg/L. This suggests that combining models and features can substantially improve predictions for TSS.

The higher errors across most models could stem from several factors. Firstly, TSS is highly influenced by site-specific environmental variables, such as varying sediment loads, water flow rates and vegetation cover (Ciancia, 2020), which may not be adequately captured in the training data. Secondly, UAV-derived data often have noise or limitations due to atmospheric interference or sensor inaccuracies, which could degrade model performance. Additionally, small sample sizes or imbalanced datasets may have constrained the models' ability to generalize effectively. The significantly better performance of Ensemble 2 suggests that it might have leveraged complementary strengths of multiple algorithms or optimized feature selection, leading to improved predictions.

Similarly, the performance metrics for predicting Chromophoric Dissolved Organic Matter (CDOM) indicate that among the individual models, Support Vector Machines (SVM) performed the best, with an RMSE value of 0.25 and an MAE value of 0.20 mg/L. Additionally, the most significant improvement was seen in Ensemble 2, which achieved an RMSE of 0.17

and an MAE of 0.12 mg/L, suggesting it effectively captured the complex relationships in the data. Conversely, models like Generalized Linear Models (GLM), k-Nearest Neighbours (k-NN), and Classification and Regression Trees (CART) showed weaker performance with RMSE values ranging from 0.26 to 0.28 mg/L. These models also showed MAE values ranging from 0.21 to 0.23 mg/L.

The reason for weaker model performances could be attributed to several factors. CDOM is a challenging parameter to predict due to its dynamic nature and dependence on multiple environmental and hydrological variables, such as organic matter composition and seasonal runoff patterns, which might not be fully represented in the training data (Ciancia, 2023, Kim et al., 2022). Additionally, UAV-derived data can be impacted by noise and limited spectral resolution, particularly in the wavelengths critical for CDOM detection. The data size and quality may also have limited the models' predictive ability. Ensemble 2's superior performance suggests that it effectively combined features or models, likely mitigating these challenges by capturing non-linear relationships and reducing overfitting.

Furthermore, the spectral indices, software and methods used played a role in the predictability of TSS and CDOM. The spectral indices derived from remote sensing data captured the optical properties of both TSS and CDOM effectively. However, their performance was influenced by only analysing a portion of the dam. TSS concentrations are typically derived from wavelengths from the red and near-infrared portions of the electromagnetic spectrum due to suspended particles reflecting scattered light Pillay et al. (2024). For this reason, the Specific Near-Infrared Index (SNIR) and the Shortwave Band Reflectance Edge index (SBRE) were chosen (Knaeps et al., 2015). Additionally, spectral indices for CDOM are derived from wavelengths in the visible and ultraviolet portions of the electromagnetic spectrum since those bands are sensitive to changes in photosynthetic activity linked to organic material in water (Rahul, 2023, Larson, 2018). Therefore, the Normalized Difference Vegetation Index (NDVI), Green Normalized Difference Vegetation Index (GNDVI) and Green Chlorophyll Index (GCI) were chosen (Viso-Vázquez, 2021). Furthermore, the use of Google Earth Engine (GEE) and RStudio were employed to harness their respective strengths in geospatial analysis and statistical modelling. GEE, a cloud-based platform, facilitated the efficient extraction and processing of multi-temporal datasets, making it crucial for mapping spatial variations in TSS and CDOM across the dam (Das et al., 2024). RStudio complemented GEE by providing advanced statistical tools for data exploration and model validation. However, RStudio's performance can be constrained by local computational limits when handling large datasets, which was a contributing factor in selecting only a portion of the dam to analyse (Wang et al., 2017). Together, these platforms provided a comprehensive framework for integrating spatial and statistical analyses. Furthermore, to ensure robust model performance, k-fold cross-validation was applied, dividing the dataset into k subsets and iteratively validating models on one subset while training on the others. This approach minimized bias and variance in performance metrics, providing reliable estimates of model accuracy, particularly with limited data. A key advantage of k-fold cross-validation is its efficient use of available data, though it can be computationally demanding when applied to large datasets or complex models (Leggesse et al., 2023).

3.4.2 Implications of the study

The findings of this study demonstrate the potential utility of drone technology in estimating surface water temperature, total suspended solids (TSS) and chromophoric dissolved organic matter (CDOM) in reservoirs, providing valuable insights for water resource management. However, the study also highlights certain limitations and implications that are particularly relevant in contexts such as South Africa. The study faced limitations due to the small sample size (Points 1-30), which limited the spatial representativeness of the findings and increased the risk of model overfitting. A great limitation was adverse weather conditions, such as high winds and rainfall, which prevented drone flights and compromised data collection, particularly in the month of May, limiting the consistency and reliability of monitoring efforts. Additionally, the limited technical expertise and skills in operating drones led to technical challenges that affected the quality and consistency of data collection. This led to partial dam coverage, which excluded areas with different hydrodynamic or ecological conditions, introducing potential biases. Furthermore, aquatic vegetation significantly influenced predictions of TSS and CDOM by contributing to CDOM through organic matter release during decomposition and attenuating sediments. However, dense vegetation also introduced spectral noise in remote sensing data, particularly in mixed water-vegetation pixels, highlighting the importance of accounting for such interactions to enhance model accuracy and interpret results effectively. Despite these limitations, the study underscores the potential for drone-derived data to provide near real-time insights into water quality parameters, enabling more informed and timely interventions.

3.5 Conclusion

The study highlights the effectiveness of predictive models and spectral indices in estimating water quality parameters, particularly TSS and CDOM, under dynamic environmental conditions. The model ensemble 2 produced superior RMSE and MAE values for both TSS and CDOM. Although the performance of the predictive models was influenced by the quality and volume of data, with limitations arising from the small sample size and technical issues, it can be concluded that UAV technology is a plausible, flexible and moderately accurate earth observation technique for monitoring water quality in small-scale applications. UAV-derived data provides high spatial resolution information, enabling researchers and stakeholders to assess key water quality parameters such as temperature, TSS, and CDOM precision more precisely. Specifically, integrating multispectral and thermal infrared UAV data can allow near real-time monitoring of aquatic systems, offering insights into seasonal dynamics and localized water quality variations. This approach supports sustainable water resource management, particularly in regions with limited access to conventional monitoring methods. However, the study's outcomes could have been further enhanced with higher spectral resolution data and additional measured testing data, which would have improved model performance and accuracy. Despite these limitations, this approach can be noted as a potential low-cost, near-real-time solution to address pressing challenges in water quality management in South Africa.

CHAPTER 4: SYNTHESIS AND CONCLUSION

4.1 A reflection of utilising UAV-derived data for water quality monitoring in small waterbodies

The water quality of small water bodies is crucial as they serve as vital sources for irrigation, livestock watering and domestic use, particularly in rural and agricultural areas (Chawla, 2020). Poor water quality can lead to reduced crop yields, clogged irrigation systems and increased maintenance costs due to sedimentation or algal growth (Morgan et al., 2020, Rajagopalan et al., 2018). Contaminants such as excess nutrients, pesticides or pathogens can also affect water safety for agricultural and human use, potentially impacting food security and public health. Additionally, small water bodies often support local biodiversity and serve as habitats for aquatic organisms essential to maintaining ecological balance. Ensuring good water quality is fundamental for sustaining the productivity of these systems, promoting sustainable water management and supporting the livelihoods of communities that rely on them (Muhoyi, 2022).

As demonstrated in this study, the use of UAV-derived data for water quality monitoring offers a promising, scalable and innovative approach to addressing key challenges in water resource management. Temperature, TSS and CDOM, as critical water quality indicators, were effectively monitored and predicted using high-resolution UAV imagery combined with advanced machine learning models, meeting the aims and objectives set out in the introduction. This integration of remote sensing and data analytics represents a significant advancement over traditional methods by offering greater spatial and temporal coverage, enabling near real-time assessments of water quality.

4.2 Overview of key findings

Temperature monitoring through UAVs provides valuable insights into thermal dynamics within aquatic systems, particularly in regions like South Africa, where climate variability plays a critical role. The UAV equipped with thermal sensors allowed for detailed spatial mapping of water temperature, revealing patterns such as localised hotspots around aquatic vegetation and seasonal variation, which have significant implications for water quality management and aquatic health (Xiao, 2023). For TSS, UAV-derived multispectral data and spectral indices such as SNIR and SBRE captured variations in sediment loads across the selected portion of the dam and predicted TSS concentrations with moderate errors (RMSE=30.50 mg/l and MAE=19,20 mg/L). This capability is particularly useful in regions experiencing seasonal rainfall and runoff events, where TSS levels can fluctuate rapidly. The UAVs' ability to map spatial heterogeneity in sediment distribution offers a powerful tool for assessing the impacts of land use changes and soil erosion on aquatic systems. Similarly, using UAVs for CDOM monitoring demonstrated the potential of remote sensing to estimate organic matter concentrations and their spatial distribution. CDOM, which strongly absorbs light in the blue and ultraviolet regions, was effectively captured using spectral indices such as NDVI, GNDVI and GCI. This allows for robust predictions despite challenges such as model overfitting. These prediction results (RMSE=0.17 mg/L and MAE=0.12 mg/L) highlight the ability of UAVs to capture optical properties, providing a better understanding of organic matter dynamics in water bodies.

Overall, the use of UAV-derived data has proven to be a transformative tool for water quality monitoring, offering high spatial resolution, flexibility and scalability. As UAV technology continues to evolve, incorporating higher spectral resolution sensors, larger datasets and improved machine learning algorithms will further enhance its potential for accurate, near real-time water quality assessments. By addressing current limitations and leveraging advancements, UAV-based monitoring can play a vital role in sustainable water resource management, particularly in regions facing significant environmental and climatic pressures.

4.3 Limitations and recommendations for future research

The application of UAV-based remote sensing for water quality monitoring, as detailed in this study, presents both the exciting potential and notable limitations. While UAV technology provides high spatial resolution and near-real-time data for assessing critical parameters like surface water temperature, total suspended solids (TSS), and Chromophoric dissolved organic matter (CDOM), several challenges hinder its full implementation and scalability. Particularly looking at this study, many limitations arose due to the small sample size, which limited the spatial representativeness of the findings and increased the risk of model overfitting. In addition, the presence of aquatic vegetation was a great disadvantage which significantly influenced predictions of TSS and CDOM. However, the dense vegetation also introduced spectral noise in the remote sensing data, particularly in mixed water-vegetation pixels, highlighting the importance of accounting for such interactions in order to enhance model accuracy and interpret results effectively.

Furthermore, a key limitation is the high cost of UAV platforms, sensors and necessary licensing. This financial barrier is particularly significant in regions like southern Africa, where funding for advanced technologies is limited (Bangira, 2024). Furthermore, the operational costs are exacerbated by concerns over equipment security, theft, and damage. Additionally, Bangira (2024) details the challenges that lay in technical expertise required for UAV operation and data analysis. The lack of trained professionals to handle these systems reduces their accessibility and usability for many stakeholders, including smallholder farmers and local governments. Lastly, UAVs face technical constraints such as limited battery life, flight ranges and sensitivity to adverse weather conditions, which can impede data collection during critical periods, such as heavy rainfall seasons. Additionally, connectivity issues, particularly in rural regions, further complicate the ability to transmit or analyse data efficiently.

These barriers highlight the need for more robust and adaptable UAV systems tailored to southern Africa's unique socio-economic and environmental contexts and similar regions. Future research should consider integrating UAV data with in-situ measurements, which can offer a comprehensive, multiscale approach to water quality monitoring. Such hybrid methods can improve accuracy, scalability and cost efficiency. Moreover, integrating advanced sensors, such as LiDAR and hyperspectral sensors, and increasing sample sizes can provide a more comprehensive understanding of complex aquatic ecosystems. Additionally, capacity building and training programs should be implemented to develop a skilled workforce capable of operating UAV systems and interpreting the collected data. Collaborative research efforts involving government bodies, academic institutions and local communities can provide interdisciplinary applications and ensure that UAV-based technologies are accessible and beneficial to a broader audience (Kowe, 2023). Expanding the scope of research to include underrepresented regions and parameters is also essential. Most studies have focused on large lakes, rivers and coastal areas, leaving smaller inland water bodies like farm reservoirs underexplored. Given their socio-economic importance, particularly for agriculture and rural development, these water bodies should be a primary focus of future research. Finally, future efforts should emphasize the socio-economic benefits of UAV-based monitoring. By demonstrating its value in improving water resource management, agricultural productivity, and environmental sustainability, researchers can build a stronger case for investment and adoption.

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