MAPPING OF WATER QUALITY PARAMETERS: A COMPARISON OF INLAND AND COASTAL SETTLEMENTS THROUGH REMOTE SENSING TECHNIQUES

Final Report

Report to the
Water Research Commission

by

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EXECUTIVE SUMMARY

The global status of water quality continues to dwindle due to the combined effects of climate change and anthropogenic factors. The compromised water quality threatens the very existence of humankind and their ability to derive a livelihood and affects their health. Furthermore, abundant contaminated water bodies serve as potential sites for both waterborne and water-related vectors, capable of transmitting various diseases to nearby communities. In sub-Saharan Africa, and South Africa in particular, numerous reports have been made of cases linked to vectors that transmit waterborne and water-related diseases, such as *Vibrio cholerae* (the cholera bacterium) and *Plasmodium falciparum* (the malaria parasite), which can be fatal. The increase in the number and spatial extent of informal settlements closer to major urban centres often increases the risk of waterborne and water-related diseases, due to poor housing infrastructure, inadequate hygiene, and a lack of proper water supply and sanitation. This problem is further exacerbated by the inherent locations of informal settlements, which often occupy marginal and ecologically sensitive areas, such as wetlands. Informal settlements are often established near small water bodies, which pose a threat to the health of the communities nearby. Monitoring water quality in the proximal water bodies of informal settlements is thus very important. However, the continued water quality monitoring in these small water bodies, located near informal settlements in South Africa, is often hindered by the inherent dangers of conducting field surveys and the inaccessibility of such water bodies. The advent of remote sensing offers the possibility of mapping water quality in informal settlements at fine spatial and temporal scales. It is therefore crucial to map not only the distribution of small water bodies around informal settlements but also to assess their quality, which often affects the settlers. This report is based on the research project entitled "*Mapping of water quality parameters: A comparison of inland and coastal settlements through remote sensing techniques.*" The research was conducted by the University of Zululand in collaboration with the Water Research Commission, University of Venda and the University of Limpopo, with project grant number C2022/2024-00809. The primary objectives of this project were to: (i) Map water quality in informal settlements by comparing the potential effects of inland and coastal water bodies on human health using remote sensing techniques. (ii) Delineate actual and potential micro water bodies present in inland and coastal informal settlements in South Africa. (iii) Identify and classify the common indicators of water quality in the informal settlements of Tshwane and eThekwini over time.

METHODOLOGY

Field surveys were conducted in the water bodies of inland and coastal informal settlements. Water samples were collected and analysed in a laboratory. Details of the field surveys and collection strategies are reported in Chapter 3. The PlanetScope (PS) data, with a high spatial resolution of 3 m (corresponding to the field data collection from informal settlements in Mamelodi, Pretoria Gardens, Diepsloot, Alexandra, and Zandspruit in Gauteng), were used in this research. Additionally, field data were collected from uMlazi informal settlement in KwaZulu-Natal. The maximum likelihood classifier (MLC) was used to classify land use/cover and to extract small open water bodies located near the informal settlements. Attempts to map water quality were also made through the weighted arithmetic water quality index (WAWQI). Additionally, various physicochemical and microbial parameters were assessed and correlated with the satellite dataset. Analyses of variance were performed to compare the parameters in the sampled water bodies across the informal settlements. Finally, a stepwise linear regression model was employed to map the spatial distribution of water

quality conditions across five informal settlements in Gauteng using various spectral indices derived from the PS data.

RESULTS AND DISCUSSION

The correlation between the PS data and water quality parameters was generally fair, with the correlation between the blue wavelength (0.49 μm) and turbidity (r = 0.61) yielding the highest correlation, whereas the lowest correlation was obtained between the presence/absence of *Salmonella* (r = 0.01) and the PS red band (0.665 μm). In the classification of land use/cover, the MLC achieved an overall accuracy of over 90%, with a kappa coefficient of 0.85. The WAWQI indicated that the water quality of small water bodies in all informal settlements is not fit for human consumption but could generally be used for other purposes, such as irrigation and industrial use (water quality index [WQI] = 13.11). The small water bodies in the northern part of Gauteng (i.e., Tshwane municipality) exhibited a higher WAWQI index than those in the southern part of Gauteng, indicating increased contamination levels around Tshwane metropolitan municipality. Physicochemical and microbial parameters differed significantly ($p < 0.05$) across informal settlements, especially in Diepsloot, Mamelodi and Zandspruit. The remote sensing modelling predicted a higher concentration of *Escherichia coli* for Alexandra than for any other inland informal settlement. In the coastal area, the PS data and heavy metals (Cd, Cu, Fe, Pb and Zn) did not correlate strongly (r < 0.42). The quality of water bodies sampled was below 12, with the majority of samples having a WQI value of approximately 6. The regression models calibrated for mapping heavy metals in uMlazi were not significant (p > 0.05), except for the Zn model, whose concentrations were below detectable levels.

GENERAL

The study demonstrated that using high spatial resolution satellite data can be beneficial when assessing water quality in the informal settlements. The main objective of this study was achieved by mapping inland small water bodies in the informal settlements. Additionally, the common water quality indicators were identified and spatially modelled across five inland informal settlements in Gauteng and one in KwaZulu-Natal. However, the study did not address the mapping of potential water bodies in the informal settlements since this objective was entirely tied to the postgraduate students' work, which has not progressed as of the writing of this report. This was due to some delay in the acquisition of datasets and other logistical difficulties. This objective will form part of future investigations and will be addressed after the conclusion of this project.

CONCLUSIONS

The study aimed to investigate the potential utility of remote sensing technology for mapping water quality in informal settlements at high spatial resolution. Findings from this research highlight the poor state of water quality in marginal areas of South Africa's urban metropolises. The results from this study may be used to guide the environmental and public health sectors within the metropolitan areas for prioritising resources needed to remediate poor water quality in informal settlements. The research findings can also be used by decision-makers to consider the efficacy of spaceborne technology and to support the configuration of future Earth observation missions in South Africa.

RECOMMENDATIONS

From this study, we make the following recommendations:

- The use of water from small water bodies located near informal settlements is discouraged, especially if it is used in an untreated state.

- Water quality parameters should be monitored timeously to quantify not only the source of contamination but also the magnitude, trend, and direction of contaminant flows.
- Although the water quality index revealed that some water within the settlements under study may be used for irrigation and industrial use, caution must be exercised when using this water for irrigation, especially due to the outbreak of cholera in South Africa.
- The utilisation of high spatial resolution remote sensing data is crucial for mapping even the smallest water bodies in informal settlements. The availability of high spatial resolution data thus enables the accurate mapping of water quality parameters.
- The accuracy of mapping water quality in informal settlements can be enhanced by the availability of high spatial and spectral resolution data, such as PS 8-band data.

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Ms Penny Jaca	Water Research Commission

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ACRONYMS & ABBREVIATIONS

ALOS PALSAR	Advanced Land Observing Satellite Phased Array L-Band Synthetic Aperture Radar
ANOVA	Analysis of variance
ASTER	Advanced spaceborne thermal emission and reflection radiometer
ALX	Alexandra
AVHRR	Advanced Very High Resolution Radiometer
CFU/mL	Colony forming units per millilitre
CDOM	Coloured dissolved organic matter
Chl-a	Chlorophyll-a
DPS	Diepsloot
DWAF	(South African) Department of Water Affairs and Forestry
EC	Electrical conductivity
MAD	Mean absolute deviation
MAM	Mamelodi and surrounding areas
MERIS	Medium resolution imaging spectrometer
MLC	Maximum likelihood classifier
MODIS	Moderate Resolution Imaging Spectroradiometer
MSI	Multispectral imager
NDVI	Normalized difference vegetation index
NDWI	Normalized difference water index
NIR	Near-infrared
NTU	Nephelometric turbidity unit
OLCI	Ocean And Land Colour Instrument
OLI	Operation Land Imager
PS	PlanetScope
PTG	Pretoria Gardens
QGIS	Quantum Geographical Information System
RMSE	Root mean square error
RV	Rappaport-Vassiliadis
SAR	Sodium absorption ratio
SAWQG	South African Water Quality Guidelines
SPOT	*Satellite Pour l'Observation de la Terre* (satellite for earth observation)
Stats SA	Statistics South Africa
TDS	Total dissolved solids
TM	Thematic Mapper
TP	Total phosphorous
TSS	Total suspended solids
UAV	Unmanned aerial vehicle (drone)
UNICEF	United Nations International Children's Emergency Fund
WAWQI	Weighted arithmetic water quality index
WHO	World Health Organization
WQI	Water quality index

GLOSSARY

Correlation:	Any relationship that exists between two variables
Heavy metals:	A group of naturally occurring metallic elements of high molecular weight and density compared to water, which can be toxic at high concentrations
Informal settlement:	Any form of housing, shelter, or settlement which is illegal, falls outside of government or municipal control or regulation, and is characterised by undeveloped infrastructure
Micro water bodies:	Small surface water bodies that are approximately 100 m^2 in diameter
Notifiable illness:	A disease or condition that is required by law to be reported to government authorities when diagnosed
Remote sensing:	The technology of acquiring information about the earth's surface without directly coming in contact with it
UAV:	Drones (aerial vehicles) that are operated remotely by an operator or autonomously for surveillance and monitoring of resources or events on the earth's surface. These vehicles do not host any human onboard.
Waterborne disease:	An illness caused by drinking water or eating food that is contaminated with human, animal faeces or other chemical compounds
Water quality:	This means the extent to which the water is suitable for specific use based on its chemical, physical or biological properties.

CHAPTER 1: BACKGROUND

1.1 INTRODUCTION

Development of informal settlements remains a challenge in South Africa, with 11% of households living in informal settlements during the 2014 fiscal year (Statistics South Africa [Stats SA], 2014). In addition to population growth, informal settlement expansions are caused by rural-urban migration of individuals in search of employment and better living conditions (UN-Habitat, 2020). However, not all informal settlements are established on optimally habitable land owing to many geopolitical and administrative factors. The recently proposed land expropriation policy by political parties in South Africa has further exacerbated many cases of immediate illegal occupation of free urban spaces in major metropolitan cities. Due to the limited space demarcated for human habitation, desperation often drives people to settle on environmentally risky land, including steep-sloped sites with high erosion potential and a high risk of flooding (Benitez et al., 2012). These types of settlements are often established without any formal town planning and with no provision of services such as sewerage, water, waste removal, electricity, roads, or recreational green spaces (Huchzermeyer and Karam, 2006).

Due to a lack of urban services, the nearby water resources tend to be polluted with litter and non-biodegradable and biological material (Govender et al., 2011; Opisa et al., 2012). These circumstances often accelerate the risks associated with water contamination, thus affecting the health of urban and peri-urban populations. Poor water quality has been documented as one of the leading causes of morbidity and mortality, while diarrhoeal disease remains the leading cause of infant and child morbidity and mortality in developing countries. In such developing countries, disease-causing pathogens are transported in streams, particularly in densely populated environments with poor sanitation, and informal settlements are no exception (Weimann and Oni, 2019). Sadly, informal settlers are trapped in a situation where they are both the culprits and victims of water and environmental pollution in their neighbourhood, thus putting the health of proximal communities at risk. A study by Darkey, et al. (2000) showed that the stream that flows through an informal settlement in Mamelodi in South Africa is odorous and contaminated, but may still be used for domestic activities, thus putting the health of the people at risk of waterborne diseases. In another study by Pretorius and De Villiers (2002), it was found that poor water in informal settlements is attributed to various factors, including poor housing conditions, which may result in poor community health associated with the contaminated water.

A crucial process that also affects the water quality in the informal settlements is urban run-off, which may contaminate local streams. This then increases the probability and the spread of waterborne diseases as a result of water pollution with organic and chemical substances that end up in nearby streams (Williams et al., 2022). Previous studies have indicated that, in dense informal settlements, stagnant water bodies often pose a major threat to the communities due to the risks associated with such water bodies acting as spreaders of diarrhoea pathogens to the environment (Nguyen et al., 2021). This is because stagnant water can harbour disease-causing pathogens and is documented to be associated with potential habitats for disease vectors such as anopheline mosquitoes (Ng'ang'a et al., 2008; Yang et al., 2019). However, although there is sufficient knowledge relating to the contribution of stagnant, contaminated water bodies to the transmission of non-communicable diseases, spatial information showing the distribution of stagnant micro water bodies in informal settlements is very limited in sub-Saharan Africa (Zerbo et al., 2022). The unavailability of such information remains a disadvantage in any government initiative to understand and respond to health risks facing informal settlements (Zerbo et al., 2020). Residents of informal settlements often obtain water from multiple sources: periodic changes in drinking-water availability, irregular supply, limited operating hours, and frequent breakdown of public water points force them to alternate between sources to meet daily water needs (Price et al., 2021). Exposure to water-related health risks varies between informal settlements. As such, spatio-temporal information on the quantity and quality of water bodies within informal settlements and the link with human health could assist in identifying potential hotspots of waterborne diseases and their temporal behaviour within and in the vicinity of informal settlements. This applies to informal settlements located in coastal areas and inland. The timely detection and monitoring of the quality of informal settlements' water resources and mapping of the physicochemical and microbial contaminants are crucial for ensuring sustainable water resources amidst the changing climate (Price et al., 2021).

Several water quality indicators have been previously used to enhance the understanding of the potential health hazards associated with these indicators. For example, Abia et al. (2015) analysed the microbial quality (*Escherichia coli*) of riverbed sediments in the Apies River in Gauteng. In that study, it was concluded that the Apies River sediments are heavily polluted with faecal indicator bacteria and that the water body may also have other microorganisms, including pathogens, which can negatively impact the population that uses the river's untreated water. In a more recent study by Gqomfa et al. (2022), the water quality of Dunoon informal settlement was analysed by assessing the concentrations of *E. coli*, mineral nutrients, and other biophysical indicators within the Diep River. The study concluded that the area under study had poor water quality, with some of the contaminants far exceeding the acceptable standards published in the South African Water Quality Guidelines (SAWQG). This further highlights the need to spatially model various water quality parameters in informal settlements to ultimately establish which segment of the population is most at risk of potential health hazards resulting from interacting with contaminated water (Edokpayi et al., 2018). Studying these patterns spatially and temporally will thus provide a key indication of suitable intervention methods for improved community health in the informal communities that studies have shown contribute significantly to the cities' labour force (Hunter and Posel, 2012).

Conventionally, monitoring of water bodies in urban and peri-urban (townships) is done through field surveys, where data pertaining to water quality indicators such as algae, *E. coli*, total coliforms, turbidity, and water temperatures are collected (Namugize et al., 2018; Pegram et al., 1999). Although this method offers more accurate water resource monitoring, it faces significant challenges when applied over large areas due to logistical constraints and the high costs associated with on-site inspections. To circumvent this challenge, aerial photography is often adopted to monitor water resources. However, the full use of this technique is also hampered by the high cost of data acquisition, time-lags, and the limited capacity of aerial data to detect variations in biophysical and biochemical constituents within peri-urban water bodies. The advent of medium to high spatial resolution earth observation data has presented new opportunities for spatially modelling various water quality parameters in recent years. For example, Ndou (2023) utilised Sentinel-2-derived data for mapping water quality indicators at Setumo Dam in the North West Province of South Africa. Modiegi et al. (2020) also emphasised the utility of Sentinel-2 derived variables and concluded that there was a strong correlation between Sentinel-2 data and water quality parameters. However, the applicability of satellites such as Sentinel-2 is limited in areas where the size of the water body is less than 10 m × 10 m. In such instances, alternative satellite data could provide more meaningful water quality mapping capabilities. For this reason, commercial nanosatellites such as PlanetScope (PS) offer an alternative to mapping water quality in cases where medium to high-resolution mapping is impractical (Mansaray et al., 2021; Vanhellemont, 2019). Based on this premise, this study aimed at mapping the water quality in the selected informal settlements of Gauteng using PS data and biogeophysical parameters.

1.2 PROJECT AIMS

This research project had the following main aims:

a) Delineate actual and potential micro water bodies present in inland and coastal informal settlements in South Africa.
b) Identify and classify the common indicators of water quality in informal settlements in Tshwane and eThekwini over time.
c) Map the water quality in the micro water bodies within urban and peri-urban areas of the Tshwane and eThekwini metropoles.

1.3 SCOPE AND LIMITATIONS

The scope of the project was to map water quality in informal settlements by comparing the water quality in the selected inland and coastal settlements of South Africa. The scope also involved:

- assessing high-resolution remote sensing techniques for mapping of micro water bodies in the informal settlements.
- identifying common biochemical and biophysical contaminants in the informal settlements under study.
- mapping the actual and potential micro water bodies in the informal settlement using geospatial techniques.
- determining whether the contamination levels varied significantly among the informal settlements, both inland and at the coast.

The limitations of the study were as follows:

- The data was collected for only a selected number of informal settlements in one province, and the concentrations found may not be representative of the unsampled (especially inland) settlements.

- The analysis was limited to the field data collected at one point in time. It did not include the spatio-temporal dynamics of contaminants, which may bring new perspectives as new evidence emerges.
- The 4-band PS data was used for the water quality analysis of the inland informal settlements, whereas the enhanced 8-band PS data is currently available for use.
- Mapping of potential micro water bodies is pending, as the relevant analysis by the postgraduate student is still underway. This work will be included in future reporting.
- No data on human diseases and associated health impacts were collected for this project.

CHAPTER 2: BACKGROUND AND LITERATURE REVIEW[1]

2.1 INTRODUCTION

Waterborne and water-related diseases are major public health concerns, causing high mortality rates in low to middle-income countries across the world. These diseases often perpetuate poverty, severe disabilities, and stigmatisation of the affected population (Freeman et al., 2013). For example, most water-related diseases (e.g. malaria) are often viewed as 'diseases of the poor', highlighting the association of such diseases with poverty (Somi and Butler, 2007; Tusting et al., 2016). In Africa, malaria mortality rates increased from 534 000 in 2019 to 602 000 in 2020 (World Health Organization [WHO], 2021). Moreover, diarrheal diseases have accounted for approximately 1.57 million mortalities in Africa, most of which were caused by *E. coli* contamination in water (Robert et al., 2021). These are just a few of the many examples of the potential threat faced by populations residing in areas where waterborne and water-related diseases are rampant. At the centre of the perpetual morbidity and mortality rates lies an uneven distribution of water bodies, poor hygiene, poor water quality, and a lack of access to safe water for domestic and recreational purposes (Oguntoke et al., 2009), especially in the low to middle-income countries of the world.

In South Africa and globally, water quality has been receiving considerable attention for its economic benefits and its role in ecosystem management and public health. Water quality refers to the physical, chemical, and biological characteristics of water (Olatinwo and Joubert, 2019). The rapid expansion of the urban population in South Africa has put a strain on the water quality in streams and water reservoirs. For example, Senbore and Oke (2021) found that changes in land use/cover in favour of urbanisation have resulted in the loss of vegetation cover and dwindling water quality in the Mangaung area of the Free State. Namugize et al. (2018) similarly reported deteriorating water quality in the uMgeni River system, specifically Midmar and Albert Falls Dams, with high *E. coli* levels attributed to settlement expansions and changing land use. In many parts of the country, deteriorating water quality has been noticeably correlated with the expansion of human settlements, especially in informal settlements, where a large population of impoverished people usually resides. For example, a recent study conducted in Diep River revealed that the average levels of *E. coli*, dissolved oxygen, electrical conductivity (EC), salinity, turbidity, chemical oxygen demand, and ammonia exceeded the recommended limits in both the wet and dry seasons (Gqomfa et al., 2022). These studies indicate that a large portion of both formal and informal populations are increasingly susceptible to the negative effects of poor water quality due to the intricate associative nature of urban and peri-urban settlements.

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[1] Based on the published article as follows: MALAHLELA OE, MOTHAPO MC, MATHIVHA FI, and HLENGWA N (2025). Progress in the application of remote sensing for water quality and human health mapping in informal settlements of South Africa: A review. *Scientific African* **28**: e02718. https://doi.org/10.1016/j.sciaf.2025.e02718

In South Africa, informal settlements comprise more than 13.5% of the total households located within urban municipalities (Stats SA, 2017). These are dwellings within the urban economic landscapes in which the arrangements are designed through marginalisation and lack of formal access to land, development, and services (Huchzermeyer and Karam, 2006). The distinctive characteristic of these dwellings is that they are often temporary structures, built from corrugated roof sheets and other makeshift materials that do not meet regulated building standards (Spinardi et al., 2020). The general housing surveys revealed that the North West Province and Gauteng have a larger number of people still living in informal settlements than any other provinces in South Africa, at 19.9% and 19.8% respectively (Figure 2.1 *a* and *b*). According to Stats SA, 12,84% of all dwellings nationally were classified as informal settlements in 2017. In terms of the metropolitan distribution, Buffalo City Municipality had the highest proportion of households living in informal settlements (26%) while Nelson Mandela Bay recorded the lowest (6.6%). Both are in the Eastern Cape (Stats SA, 2017). However, due to the constant mobility of residents and the land tenure of the informal settlements, it is highly likely that the actual number of households is significantly higher than estimated (Parikh et al., 2020). Most informal settlements are characterised by very narrow routes, often untarred, making it difficult to render essential services such as refuse removal for waste management. This results in unprecedented levels of plastic and other solid waste materials accumulating, which further reduces the aesthetic quality of these settlements. Additionally, informal settlements tend to suffer from uncollected and/or illegally dumped soiled nappies, food waste, sand, gravel, paper, plastic packaging, metal, and glass, which contribute to several environmental impacts (Haywood et al., 2021). A high proportion of informal settlements are characterised by high levels of vulnerability to fire hazards, illegal electrical supply connections, flood hazards and topographic instability (Parikh et al., 2020).

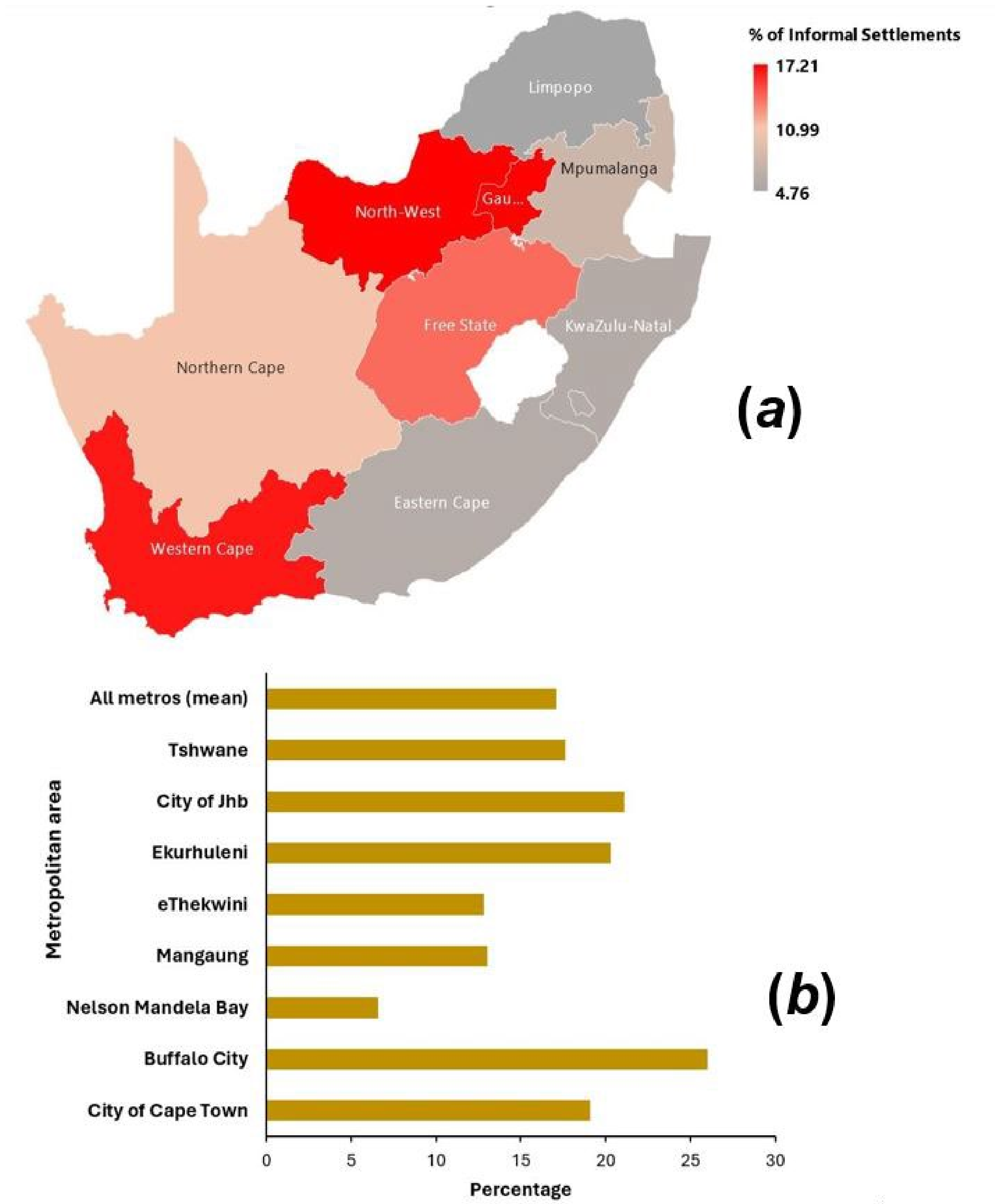

Figure 2.1. (a) The average percentage of households found in informal settlements in South Africa per province. (b) Percentage of households found in informal settlements across metropolitan areas of South Africa. Source: Stats SA (2017)

City development and industrial area expansion in South Africa have led to increased demand for freshwater and services for the proximal urban population. Unfortunately, the ever-increasing urban population inhabit even the most hazardous areas with poor hygiene and sanitation (Gqomfa et al., 2022), which ultimately threatens available water resources and nearby wetlands.

Consequently, an improved understanding of the potential effects of water quality on the public health of communities residing in informal settlements is critical for improved health interventions and environmental management. In recent decades, many countries have adopted technology for assessing water quality, disease spread, and informal settlement expansion. The use of airborne and spaceborne technologies has received considerable attention in epidemiological and demographic studies alike since the launch of the first Earth Resources Technology Satellite (ERTS-1) in 1972. Therefore, this review was aimed at discussing the progress made in assessing water quality with regard to informal settlements in South Africa. It further discusses how remote sensing techniques have been applied in the assessment of water-related morbidity in the informal settlements and the potential risks associated with contaminated water sources in such settlements (Figure 2.2). This review also highlights the prospects and future opportunities available within the remote sensing domain for public health applications.

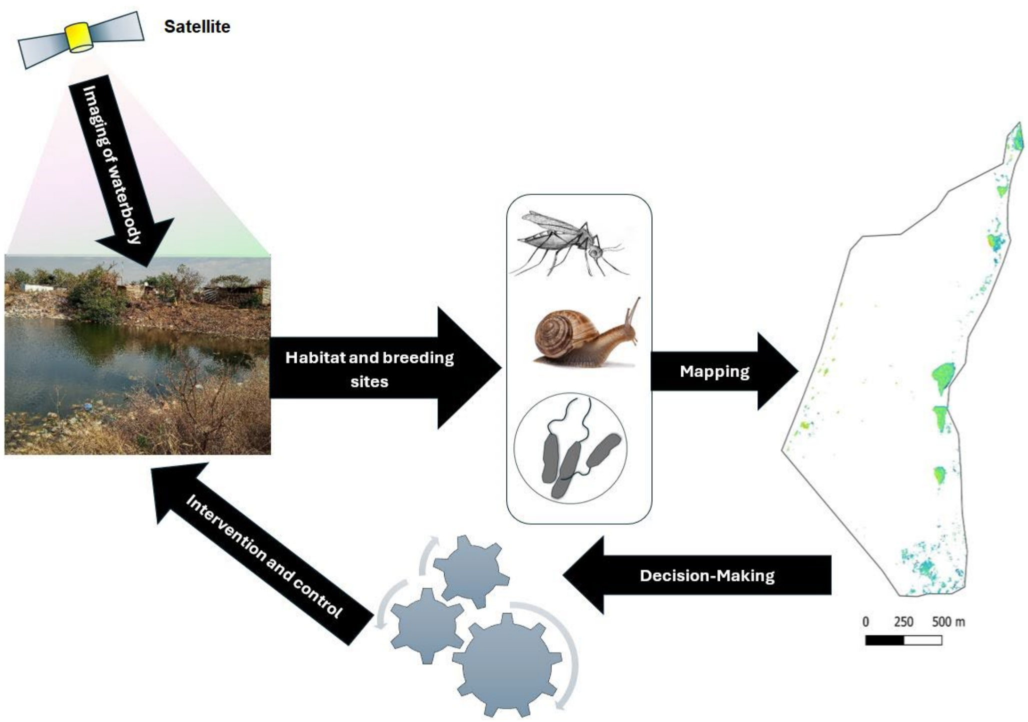

Figure 2.2. Overview of remote sensing for application in epidemiological studies. Credits: Some illustrations of organisms were obtained from www.pinterest.com.

2.2 REVIEW METHODS

This review article adapted a search methodology following Feil et al. (2019). The aim was to collate, analyse, and discuss pertinent information contained within various publications to provide an overview of the advancement in remote sensing technology for mapping water quality in South Africa's informal settlements, with emphasis on the spread of waterborne diseases. Articles were selected systematically following the preferred reporting items for systematic reviews and metaanalyses flow diagram (Page et al., 2020) as outlined in Figure 2.3. Specific keywords were used to search for articles used in the review. These included *remote sensing*, *water quantity mapping*, *water quality and human health*, *the effects of water quality on human health in South Africa informal settlements*, *remote sensing and water quality mapping*, *waterborne disease and water quality*, and *informal settlements in South Africa*. By using specific keyword strings, we identified 200 articles from databases (i.e. Google Scholar and Web of Science) and manual searches (i.e. Research Rabbit and Connected Papers).

One criterion for eligibility was that an article must reflect a string of one or more keywords for retrieval. This was in addition to the relevance of the article to the field of remote sensing applications. This review only considered articles published in the English language; hence, three articles that were not published in their entirety in English were excluded at the screening stage. In addition, 28 articles were excluded because the outcomes were irrelevant or the data analysed did not pertain to the current review. A total of 157 published articles were reviewed, providing a holistic overview of advances in utilising remote sensing for mapping water quality in different environments. Of the 157 articles included, 18 were used to populate the introduction and methods section and the remaining 139 were used to synthesise the review findings. Figure 2.4 presents the time of publication of the selected articles, which ranges from 1982 to 2024, with the most articles published in 2020. It also shows the projected publication trend based on the available number of published articles. VOSViewer (v 1.6.20, Centre for Science and Technology Studies, Leiden University) was used to depict the visual relationship between keywords and to assess the frequency of the keywords (and themes) within the analysed literature (Van Eck and Waltman, 2017).

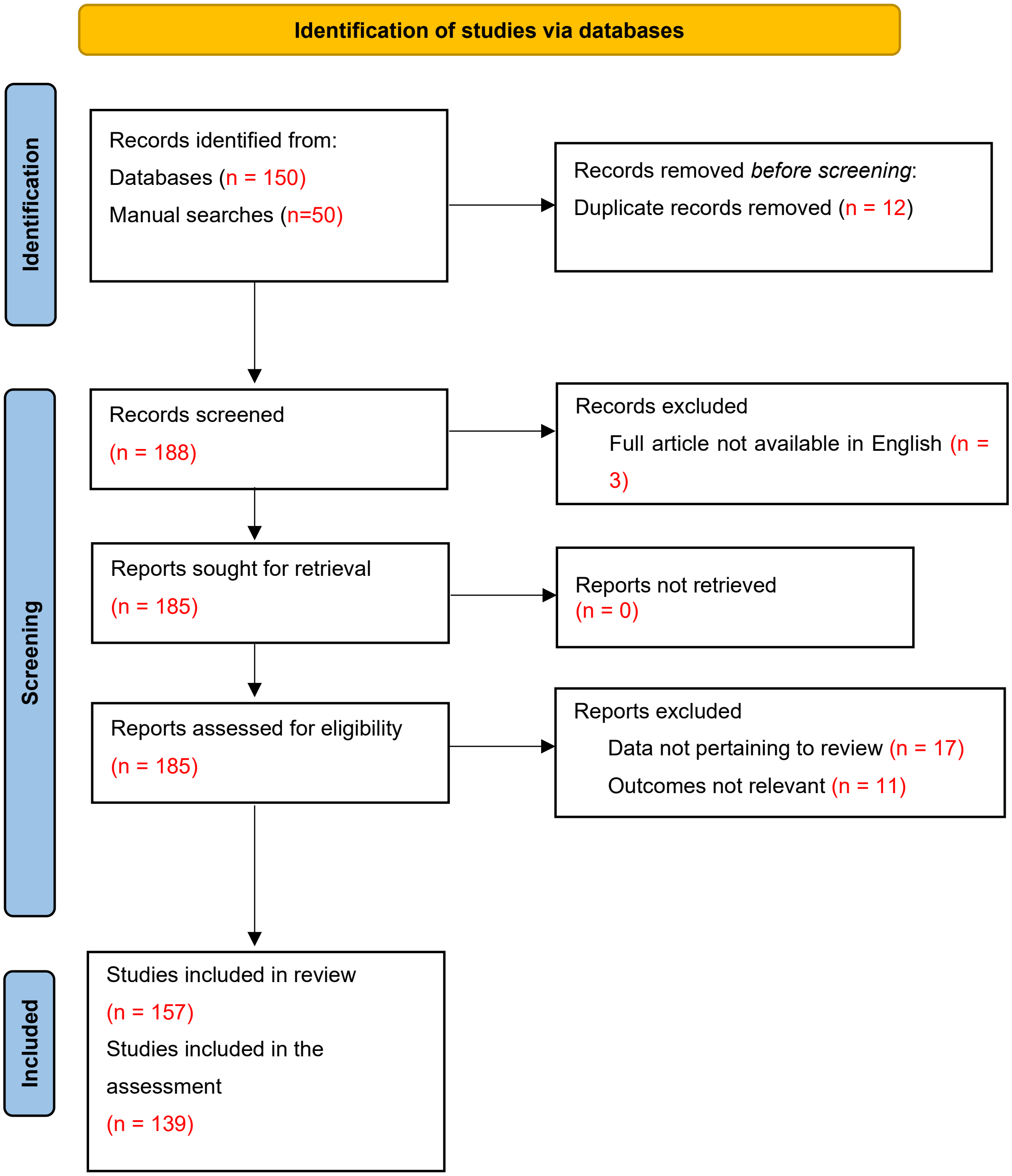

Figure 2.3. Article selection process

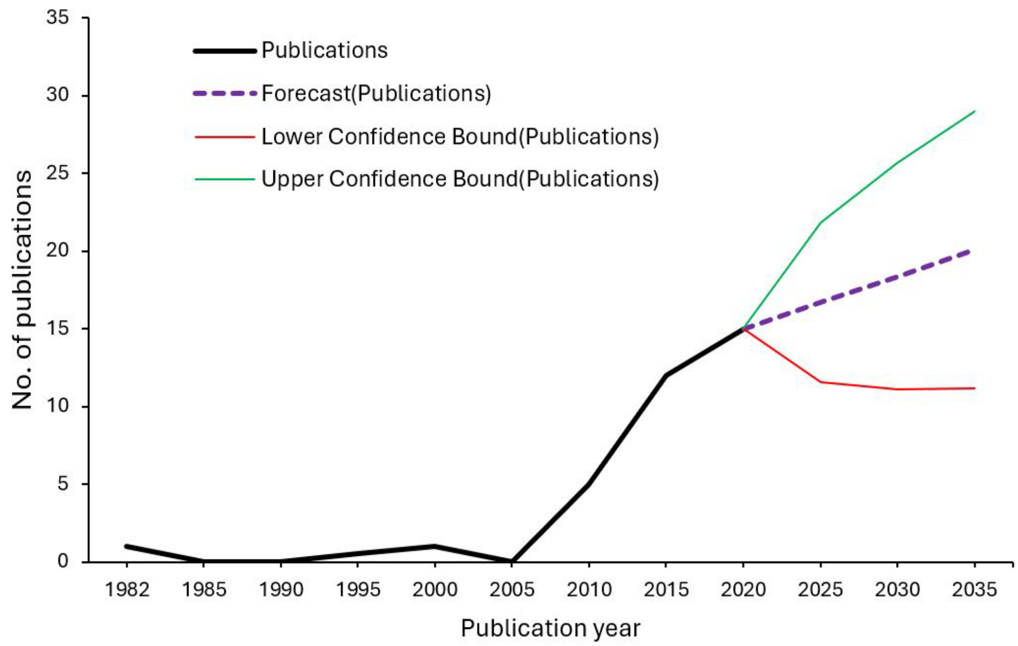

Figure 2.4. Timeline of publications considered in the review findings analysis and the forecasted publications

2.3 REVIEW FINDINGS

2.3.1 Water quality in informal settlements

Standards for water quality in South Africa were legislated through the promulgation of the National Water Act No. 36 of 1998. This Act makes provisions for what is acceptable in terms of water quality for recreational, industrial, ecosystem, agricultural, and domestic use. The guidelines and standards set out in the Act provide limits of acceptable constituents in water for domestic use, and such constituents include algae (phytoplankton and associated periphyton), aluminium, ammonium, arsenic, dissolved organic carbon, and other microbial organisms, among others (Department of Water Affairs and Forestry [DWAF], 1996). For this review, we refer to water quality as the biophysical and biochemical constituents of water found in streams, pools, wetlands, and any stagnant water bodies that occur in or near informal settlements. The assessment of water quality along municipal servitudes is excluded from this current literature review. It is important to review the water quality in these settlements, considering that informal settlements often encroach on ecologically sensitive areas such as wetlands (Adegun, 2019) and river systems (Fitchett, 2017; Gqomfa et al., 2022) and that these settlements often comprise many stagnant water bodies (Carruthers, 2008). The establishment and proliferation of informal settlements in South Africa threaten aquatic ecosystems and the health of the communities that reside in them, mainly due to the effects of pollution and the bioaccumulation of harmful contaminants in nearby streams (Maboza et al., 2013).

In a recent study by Gqomfa et al. (2022) it was concluded that overcrowded informal settlements with inadequate sanitation have significantly contributed to the substantially high levels of *E. coli*, and dissolved oxygen, salinity, turbidity, EC, and chemical oxygen demand levels that exceeded the recommended limits in the wet and dry seasons in the Diep River in the Western Cape. In that study, a major decline in the water quality was observed in areas of the river close to the informal settlement of Dunoon, suggesting that the informal settlement contributed to the poor water quality in nearby streams. Fatoki et al. (2001) observed that the levels of faecal coliforms at all sampled sites along the Umtata River (most of which were informal settlements) were significantly higher than the recommended national guidelines. Such a situation poses a threat to the health of the communities that are located at or near such a water body. In another study conducted in the North-West province, Jordaan and Bezuidenhout (2015) observed that not only does wastewater enter the river systems of the Mooi River through agriculture and mining, but also from the run-off of wastewater from informal settlements that are located near a tributary, the Wonderfontein Spruit river channel. The pyrosequencing and subsequent analysis in that study also showed that nutrient inputs and faecal pollution strongly impacted the physicochemical and microbiological quality at the downstream sites.

The perilous water quality found in the informal settlements of Dunoon in the Western Cape, Umtata informal settlements in the Eastern Cape, and along the Mooi River system in the North-West Province is not unique to these areas. Notwithstanding, it is apparent that a large proportion of the informal settlements in the country experience similar water quality challenges because of the lack of access to proper sanitation (Muanda et al., 2020; Pan et al., 2015), overpopulation (Gqomfa et al., 2022; Visagie and Turok, 2020), poor service delivery and policy implementation (Taing, 2019), poor infrastructure (Vearey et al., 2010; Weimann and Oni, 2019) and the heightened desperation for housing (Marutlulle, 2017). Previous studies have concentrated on several indicators of water quality in these settlements, including *E. coli*, coliforms, water temperature, pH, chlorophyll-a (chl-a), salinity, turbidity, and CDOM levels, among others (Jordaan and Bezuidenhout, 2015). In all the studies that formed part of this review, these parameters were recorded to be much higher than the recommended national guidelines for a water body, which potentially poses a threat to the public health of the informal settlers who often get in contact with such contaminated water bodies, especially during flooding (Gqomfa et al., 2022; Mbonambi, 2016). This situation poses potential health risks, as it could lead to waterborne and water-related diseases, ultimately affecting the workforce in South Africa's metropolitan areas.

2.3.2 Mapping of water quality

Water quality is mapped primarily for environmental protection, effective planning and management, and equitable water allocation, among other purposes. Several approaches have been adopted for mapping water quality, including (i) ground-based surveys, (ii) geographical information systems (GIS) and (iii) remote sensing technologies. The ground-based surveys provide a detailed assessment of water quality parameters that include the physicochemical and biological constituents present in any given water body. Ground-based surveys are conducted when researchers collect in-situ data about water quality, including CDOM, turbidity, salinity, total dissolved solids (TDS), temperature, chl-a, pH, mineral nutrients, optical water type, coliforms, and *E. coli*, among others (Madilonga et al., 2021). In this way, the water quality data will be subjected to various statistical analyses to assess the distribution of water quality parameters in a water body. Such methods include the principal component and discriminant function analyses, linear regression, and hierarchical classification analysis, among others (Akin et al., 2011; Lu et al., 2019). They are very effective for assessing the water quality of a given water body, but their effectiveness is hampered by the costly nature of field surveys, which could force researchers to collect a limited number of samples to make conclusive deductions about the water quality of a given water body (Babitsch and Sundermann, 2020). Another factor that serves as a limitation for field-based assessments is the need to transport samples to laboratories for analysis, which introduces delays for large-scale and high-frequency water quality assessments (Dube et al., 2015). Finally, field surveys are only practical for smaller water bodies, as larger water bodies pose much bigger challenges for accurate water quality assessment. These logistical and technical challenges have paved the way for the GIS approach due to its ability to spatially interpolate water quality parameters over a larger water body (Oseke et al., 2021).

Among the most used GIS approaches for mapping water quality are spatial interpolation methods, such as kriging and inverse distance weighting, which have been used predominantly for groundwater quality assessment in South Africa (Dube et al., 2020; Molekoa et al., 2019). Although the spatial interpolation GIS techniques are commonly used for mapping water quality in South Africa and globally, their utility is limited by the disadvantages associated with the ‘bull’s eye’ effect in interpolation (Chen et al., 2016). Interestingly, there is no record (that we are aware of) of studies that seek to assess water quality in the informal settlements of South Africa through these approaches, likely because of the focus on ground-based assessments for water quality. Many researchers adopt the use of remotely sensed data that is available at various spatio-temporal and spectral resolutions to circumvent the limitations of both field-based and GIS assessments of water quality.

Remote sensing has emerged as a reliable, time- and cost-effective technology for mapping and continuously monitoring water quality parameters at various scales (Adjovu et al., 2023; Bangira et al., 2023; Dube et al., 2015). Globally, it has been increasingly lauded as an efficient alternative for mapping water quality. Currently, numerous ground-based (e.g. field spectroradiometers), airborne, and spaceborne remote sensors are being tested worldwide for assessing water quality parameters such as chlorophyll, turbidity, total suspended solids (TSS), sodium absorption ratio, and CDOM (see Yan et al., 2023; Yang et al., 2022). Spaceborne multispectral mapping sensors, such as Landsat, Sentinel, Moderate Resolution Imaging Spectroradiometer (MODIS), and Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER), offer synoptic spectral data in a few broad and non-contiguous spectral ranges of the electromagnetic spectrum, with a single band representing the average of a wide spectral region. Their application in water quality mapping assumes that specific wavelengths can reflect the properties of water, and a slight modification in water quality can alter the spectral signature of pure water. For instance, the red and green bands are particularly sensitive to chl-a, a key indicator of algal biomass, while the near-infrared (NIR) band is used to detect suspended solids and turbidity. As such, high concentrations of chl-a result in increased reflectance in the green (~560 nm) and red-edge (~700 nm) bands, making it possible to map harmful algal blooms and eutrophication events across large water bodies (Ali et al., 2022; Obaid et al., 2021; Sakuno et al., 2018). Based on these premises, remote sensing technologies are widely used to detect and explain spatial variability in water quality.

In South Africa, the capabilities of multispectral remote sensing sets such as the medium resolution imaging spectrometer (MERIS; Matthews, 2014; Matthews and Bernard, 2013, 2015; Matthews et al., 2010, 2012), ASTER (Modiegi et al; 2020), *Satellite Pour l'Observation de la Terre* (SPOT; Modiegi et al., 2020; Munyati, 2015), MODIS (Malahlela et al., 2018a), Sentinel Multispectral Imager (MSI; Bande et al., 2018; Modiegi et al., 2020; Ndou, 2023; Obaid et al., 2021; Sakuno et al., 2018;), Ocean and Land Colour Instrument (OLCI; Kravitz et al., 2020), Landsat Thematic Mapper (TM) (Oberholster and Botha, 2010), and Operation Land Imager (OLI; Bande et al., 2018; Malahlela et al., 2018b; Modiegi et al., 2020; Obaid et al., 2021, 2024) in detecting and mapping water quality parameters such as chl-a, dissolved oxygen, CDOM, TSS, nitrates, organic nitrogen, phosphates, total phosphorus, fluoride, and sulphates have been explored. Table 2.1 provides a summary of the remote sensing applications in detecting and mapping water quality parameters in South Africa. Numerous studies have been conducted using free and open satellite imagery to detect and map water quality parameters. Perhaps one of the most notable efforts to monitor inland water quality through remote sensing in South Africa was that of Matthews et al. (2010). In that study, MERIS data were used alongside the Inverse Radiative Transfer Model Neural Network algorithm and linear and non-linear regression models to assess the temporal variability of chl-a concentrations, TSS, CDOM, and the Secchi disc depth in Zeekoevlei lake. This review further revealed that chl-a is the most widely detected parameter in South African water bodies (e.g. Kravitz et al., 2020; Malahlela et al., 2018a; Matthews, 2014; Matthews and Bernard, 2013, 2015; Matthews et al., 2012), specifically as a proxy for harmful algal blooms, as compared to other parameters. For instance, Malahlela et al. (2018a) employed the visible to NIR spectral bands of Landsat 8 OLI to map chl-a concentrations within the Vaal Dam, which is an economically significant dam in South Africa. This study used a stepwise logistic regression model to classify various concentrations of chl-a in the reservoir. The numerous chl-a studies in South Africa could be attributed to the persistent problem of algae, water hyacinth, and cyanobacteria prevalence in many reservoirs, which interrupts adequate freshwater supply across the country. The literature further indicates that numerous studies have been conducted primarily to compare the spatial and spectral capability of common remote sensing instruments such as Landsat and Sentinel-2. For example, Bande et al. (2018) concluded that Sentinel-2 data yield higher mapping accuracies of chl-a and turbidity in the Vaal Dam than Landsat 8 data due to the higher spatial resolution of Sentinel-2 data. More recently, Obaid et al. (2021) concluded that different spectral regions of Landsat and Sentinel-2 are capable of mapping chl-a concentrations and total suspended materials at much higher accuracies, thus improving long-term and near-real-time monitoring of water quality in water bodies such as the Vaal Dam reservoir.

Monitoring water health as part of water management in South Africa is important, as evidenced by one of the most successful water quality projects in South Africa, a joint initiative by the Departments of Water and Sanitation and Science and Technology and the Water Research

Commission. This initiative aimed to integrate remote sensing into the National Eutrophication Monitoring Programme, which started in 2015 as the EONEMP K5/2458 Project. This initiative has, for the first time, demonstrated the possibility of continuous monitoring of water quality across major water bodies in South Africa by mapping cyanobacterial blooms (Matthews, 2018). This project depends on the continuous input of Sentinel-3 OLCI data with 21 spectral bands at a 300 m spatial resolution (Table 2.1). This resolution is optimal for mapping water quality parameters in larger water bodies (e.g. 300 x 300 m; Toming et al., 2017). However, the application of Sentinel-3 is impractical for mapping water quality of informal settlements in South Africa, such as puddles, springs, ditches, and flushes, which are typically less than 100 m^2 in area. For this reason, finer resolution data such as PS could provide alternatives for mapping water bodies and water qualities at the scales that are otherwise not offered by high spectral resolution satellites such as Landsat 8 and Sentinel-2/3 (Mansaray et al., 2021). The use of the PS data has shown great potential elsewhere but has not been explored in South Africa, especially for informal settlement mapping, due to the commercial nature of the data and the availability of other alternative remote sensing data sources (Mishra et al., 2020; Vanhellemont, 2019). The complexity of environmental issues that threaten the communities residing in informal settlements is crucial to understanding the extent to which high-resolution remote sensing could be used in addition to field assessments of water quality in such settlements (Mudau and Mhangara, 2021). A comprehensive review of remote sensing applications for mapping the waterborne and water-related diseases is needed to understand actual and potential environmental risks faced by the people living in informal settlements. This thus provides a basis for determining the contribution of remote sensing technology for societal benefits and for environmental monitoring – a concept that motivates the launch of many modern-day remote sensing instruments into space (Ustin and Middleton, 2021).

In our review, we found many articles published between 2014 and 2023. In the analysis, *remote sensing* was the common keyword, followed by *water quality*, which is closely related to both *remote sensing* and *chlorophyll-a* (Figure 2.5).

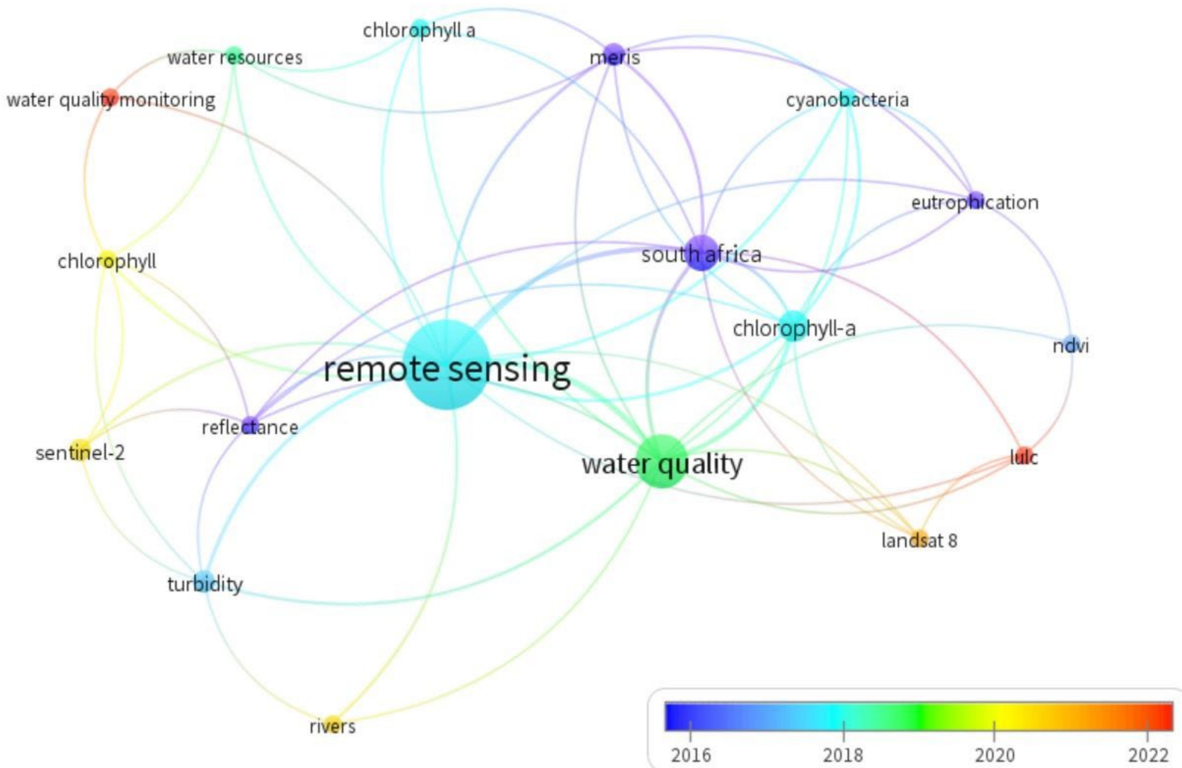

Figure 2.5. Overlay visualisation of the association among commonly occurring keywords from the analysis conducted in this research

2.3.3 Common datasets and methods

Remote sensing datasets and their derivatives play a critical role in spectral discrimination between objects. Therefore, they are effective in detecting, mapping, and monitoring the distribution of earth features. As such, several sensors' spectral bands, spectral ratios, and spectral indices have been tested in detecting the presence and mapping the spatial distribution of specific water quality parameters in South African water bodies (Malahlela et al., 2018; Obaid et al., 2021). For example, Malahlela et al. (2018) used remote sensing indices (difference vegetation index, particularly two-band indices in the red-NIR region) and the individual spectral bands of Landsat OLI and MODIS to estimate chl-a in the turbid Vaal Dam water. Their findings reveal that the difference vegetation index was the only significant (0.0027; $\rho < 0.018$) remote sensing variable for predicting chl-a in the Vaal Dam. They argued that remote sensing indices are better than individual spectral bands designed for mapping changes in chl-a because of the indices' ability to compensate for errors resulting from solar or viewing geometry. Similarly, Obaid et al. (2021) suggested that the application of band ratios removes systematic errors while minimising atmospheric effects.

Empirical methods such as regression analysis and classification algorithms have proven effective in predicting and subsequently mapping water quality parameters worldwide. In South

Africa, empirical analytical techniques have been employed to model water quality parameters and evaluate the accuracy of multispectral data and its derivatives in predicting those parameters (Bande et al., 2018; Karaoui et al., 2019; Matthews and Bernard, 2015;). These include techniques such as linear regression (Matthews and Bernard, 2015), stepwise regression (Karaoui et al., 2019), and partial least squares regression (Bande et al., 2018). However, over 20 years of scientific inquiry on water quality mapping in the country, empirical methods have been predominantly used, with limited methodological diversity. Few studies have employed classification algorithms to map water quality parameters. Some of those algorithms were employed to manipulate specific sensor datasets, while others are based on band ratios that are argued to remove systematic errors and minimise atmospheric effects (Obaid et al., 2021). For instance, Matthews and Bernard (2015) used the maximum peak height algorithm to provide quantitative chl-a estimates and to discriminate it in the water bodies on MERIS imagery (Table 2.2). Unlike empirical methods, algorithms have emerged as proxies to conventional parametric algorithms; however, they produce high classification accuracies and are more accurate and capable of processing large datasets (Thamaga and Dube, 2018).

Table 2.1. Summary of the remote sensing applications in detecting and mapping water quality parameters in South Africa

Author(s)	Waterbody under study	Sensors used	Methods used to analyse data	Parameter studied	Optimal bands	Results (R^2)
Matthews and Bernard (2015)	50 water bodies (including rivers, lakes, and dams)	MERIS	Maximum peak height algorithm Time series (2002-2012)	Chl-*a*	440–770	> 0.7
Matthews (2014)	50 water bodies (including rivers, lakes, and dams)	MERIS	Maximum peak height algorithm Time series analysis (2002-2012)	Chl-*a*	440–770	0.64
Matthews and Bernard (2013)	Hartbeespoort, Loskop, and Theewaterskloo f dams	MERIS	Pearson correlation	Chl-*a*	664–885	0.58
Matthews et al. (2012)	Zeekoevlei, Hartbeespoort, and Loskop	MERIS		Chl-*a*	681, 709, and 753	0.71

	dams and Southern Benguela ocean		Maximum peak height algorithm			
Matthews et al. (2010)	Zeekoevlei Dam	MERIS	Iterative Retrieval of Transmittance and Multiplicative Normalisation Network algorithms	Chl-*a*	440–770	0.96
				TSS		0.76
				Clarity		0.8
				CDOM		0.75
Munyati (2015)	Modimola Reservoir, Cooke's Lake, and Lotlamoreng and Disaneng reservoirs	SPOT 5	Geostatistical analysis and kriging interpolation	NO_3	780–890	0.12
				PO_4		0.21
Sakuno et al. (2018)	Vaal Dam	Sentinel-2	1-, 2-, and 3-band ratio semi-analytical algorithms	Chl-*a*	400–900	0.51
				Turbidity	775 and 740	0.77
			Linear and non-linear trends			
Kravitz et al. (2020)	Vaal, Hartbeespoort, Roodeplaat, and Bronkorspruit dams	Sentinel-3 OLCI	Band ratio semi-analytical algorithms	Chl-*a*	709	0.55
Ndou (2023)	Setumo Dam	Sentinel-2	Linear regression analysis	EC	Band 4	0.7
				TDS	Band 11	0.6

				pH	Band 5	0.6
				Turbidity	Band 3	0.7
Oberholster and Botha (2010)	Hartbeespoort Dam	Landsat 5 TM	Band ratios	Chl-*a*	675	0.5–0.77
Obaid et al. (2024)	Vaal Dam	Landsat 8 OLI	Time series/trend analysis (2000–2010)	Chl-*a*	-	-
				TP	-	-
				Organic nitrogen	-	-
				Water temperatur e	-	-
Bande et al. (2018)	Vaal Dam	Landsat 8 OLI	Partial least squares regression	Chl-*a*	B4/B1, B4/B2, B2/4	0.59, 0.50
		Sentinel-2		Turbidity	Band 1,2,3, and 4	0.86, 0.68
Obaid et al. (2021)	Vaal Dam	Landsat 8 OLI	Regression	Chl-*a*	560, 443	0.89
		Sentinel-2			705, 665	0.75
Ali et al. (2023)	Hartbeespoort Dam	Landsat 8 OLI	Regression analysis	Chl-*a*	-	0.86
		Sentinel-2	Time series/trend analysis (1980–2020)			

Malahlela et al. (2018)	Vaal Dam	MODIS Landsat OLI	Stepwise logistic regression	Chl-a	640–880	0.65–0.83
Modiegi et al. (2020)	Mooi River	Landsat 8	, Regression analysis	SAR	600–790	0.98
		Sentinel-2		Fluoride		0.79
		ASTER		Sulphate		0.79
		SPOT 6		Potassium		0.77

CDOM, coloured dissolved organic matter; Chl-a, chlorophyll-a; EC, electrical conductivity; MERIS, Medium resolution imaging spectrometer; OLCI, Ocean and Land Colour Instrument; OLI, Operation Land Imager; SAR, sodium absorption ratio; SPOT, *Satellite Pour l'Observation de la Terre*; TDS, total dissolved solids; TM, Thematic Mapper; TP, total phosphorous; TSS, total suspended solids

Table 2.2. Specifications of sensors used to detect and map water quality parameters in South Africa

Sensor	Spatial resolution (m)	No. of spectral bands	Description	Swath width (km)	Temporal resolution (days)
MERIS	300	15	All	1 150	3
SPOT 6	6	4	Band 1–3	60	1–4
	1.5		Panchromatic		
SPOT 5	10	5	Band 1–3	60	2.5
	20		Band 4		
	2.5		Panchromatic		
Landsat 5 TM	30	7	Band 1–5, 7	185	26

	120		Band 6		
Landsat 8 OLI	30	9	Band 1–7, 9	185	16
	15		Band 8		
Sentinel-3 OLCI	300	21	All	1 270	1–2
Sentinel-2 MSI	10	13	Band 2,3,4, and 8	290	5
	20		Bands 5, 6, 7, 8A, 11, and 12		
	60		Bands 1, 9, and 10		
ASTER	15	14	Band 1–3	60	16
	30		Band 4–9		
	90		Band 10–14		

ASTER, Advanced spaceborne thermal emission and reflection radiometer; MERIS, Medium resolution imaging spectrometer; MSI, multispectral imager; OLCI,Ocean and Land Colour Instrument; OLI, Operation Land Imager; SPOT, *Satellite Pour l'Observation de la Terre*; TM, Thematic Mapper

2.3.4 Reality of waterborne diseases in South Africa

Waterborne diseases pose a significant public health risk globally, with a particularly high burden in third-world or middle-income countries, including South Africa (Gwija, 2021). While these diseases threaten all populations, certain groups (such as immunocompromised individuals, HIV-positive children, and the elderly) are especially vulnerable (Kombo Mpindou et al., 2021). Waterborne diseases are considered critical indicators of health in the most deprived populations, reflecting disparities in access to clean water and sanitation (Tseole et al., 2022). According to the WHO, 844 million people lack access to basic drinking-water services globally, while UNICEF (United Nations International Children's Emergency Fund) reported in 2017 that 2.1 billion people worldwide did not have access to safe drinking water, often contaminated by faeces and other pollutants (WHO, 2021). In South Africa, waterborne diseases such as gastroenteritis, cholera, viral hepatitis, typhoid fever, bilharziasis, and dysentery remain significant threats (Moslen et al., 2024).

The global impact of waterborne diseases is stark. The WHO estimates that diarrheal diseases claim 1.5 million lives annually, with 502 000 deaths linked specifically to contaminated drinking water (Szálkai, 2023). An additional 842 000 deaths, including 361 000 children under five, are attributed to poor sanitation and inadequate hygiene practices, resulting in diseases such as cholera, dysentery, and typhoid fever (WHO, 2014). The African continent bears the heaviest burden, with 45.8 deaths per 100 000 attributed to water, sanitation, and hygiene-preventable diseases, as compared to 10.6 and 15.4 in the eastern Mediterranean and Southeast Asia, respectively (WHO, 2020). Factors contributing to waterborne disease outbreaks include both man-made activities and natural phenomena, such as climate change, water stress, and the inadequate treatment of contaminated groundwater (Zerbo, 2022). These factors exacerbate the prevalence of microbiologically unsafe water, posing severe threats to public health through the spread of infectious diseases, increased morbidity, and mortality. Addressing waterborne diseases requires prioritising equitable access to safe water, improving sanitation, and mitigating the impact of environmental and societal factors driving these outbreaks.

2.3.5 Waterborne diseases mapping

Cholera, a common waterborne disease, has been the subject of substantial research in epidemiology, microbiology, and public health. Cholera is an acute diarrheal illness caused by consuming water or food contaminated with *Vibrio cholerae* strains. Because of their relationship with zooplankton and phytoplankton, which serve as important reservoirs for infection, certain *V. cholerae* viruses may exist in ambient water sources outside of the human system (Penrose et al., 2010). The spread of cholera in informal communities has been linked to high population density, a lack of basic sanitation, and polluted drinking wells (Eurien et al., 2021; Penrose et al., 2010). In South Africa, cholera was first documented in 1890 in Durban, KwaZulu-Natal (Seedat, 1982). Since then, there have been countless reports of transmission in other places; however, they have never been documented. However, in 2008, a major cholera outbreak was reported that started in Zimbabwe, with more than 73 000 cases and a case fatality rate of 4.7% (3 500) (Mintz and Guerrant, 2009). Subsequently, as many as 12 706 cases were reported in South Africa, mostly in Mpumalanga (54%) and Limpopo (43%) between 15 November 2008 and 30 April 2009 (Ismael et al., 2013). The increase in cholera cases was largely attributed to the heavy rains recorded just before the start of the cholera epidemic, which resulted in the contamination of water sources due to surface run-off (Sigudu et al., 2015). However, since the major cholera outbreak in 2008, there have not been any significant cases and fatalities in South Africa, largely due to the improved water service delivery to many parts of the country. However, this should not be taken to mean that the *V. cholerae* pathogen no longer lurks in the environment, particularly in water bodies in informal settlements where population density is high (Penrose et al., 2010). Cholera was initially mapped by Dr John Snow, a medical geographer, in 1854 in London using a GIS approach (Musa et al., 2013). Since then, many researchers have adopted the GIS approach with very limited consideration of the relationship between cholera-related phytoplankton and remote sensing (Xu et al., 2015). For this review, we did not find any literature that focused on mapping cholera outbreaks using remote sensing in South Africa. However, some studies were conducted elsewhere in Africa, such as those of Luquero et al. (2011) and Moore et al. (2017) in Guinea-Bissau and the African continent, respectively, which demonstrated the capability of satellite remote sensing for monitoring shifts in cholera-associated environmental and climatic factors. The lack of studies in the southern African context thus presents an opportunity to test the utility of remote sensing techniques, especially since most of the countries in this region are still developing, with slums and informal settlements being a consistent feature around major cities.

Typhoid fever, caused by *Salmonella enterica* (*S.* Typhi), is another notifiable illness in South Africa, although it has a relatively low endemicity and is associated with low death and infection rates. Keddy et al. (2016) reported that the case fatality rate of typhoid fever in South Africa had decreased from 15.5% to 1.1% between 1945 and 1977. However, more recent laboratory-based surveillance studies have indicated that the mortality rate may have been approximately 6.8% between 2003 and 2013 (Keddy et al., 2016, 2018). Although typhoid fever has low infection rates, it is considered one of the most severe *Salmonella* infections, which is caused by diarrhoea and systemic diseases (Hanan et al., 2021). Its outbreaks occur in densely populated and vulnerable areas, such as informal settlements with poor sanitation and crowded conditions (Keddy et al., 2018). Since 2003, no more than 250 cases of enteric typhoid fever per year have been reported nationally, with the fewest cases reported in the 2022 outbreak. Currently, Gauteng and the Western Cape account for the highest number of confirmed typhoid fever cases, while there are emerging reports of infections in Kenneth Kaunda Municipality in the North-West Province (National Institute for Communicable Diseases, 2022). Perhaps the most notable mapping of typhoid fever in South Africa can be found in Makungo et al. (2020), in which the suspected and confirmed typhoid fever cases and water sources in Sekhukhune District were mapped using GIS. Typhoid fever mapping through remote sensing or the integration of remote sensing data and GIS has never been done in South Africa, especially in informal settlements. The under-utilisation of remote sensing data and approaches can be attributed to the technical complexities for non-experts and the limited accessibility of high-resolution data, which is often restricted by high acquisition costs. Additionally, the presence of *S. enterica* in contaminated water bodies might not have significantly strong spectral activity due to the combination of various water quality parameters such as turbidity, coloured dissolved organic matter (CDOM), phycocyanin, suspended solids and chl-a, which are known to be more spectrally active than the concentration of *S. enterica* species (Vakili and Amanolahhi, 2020)

Dysentery, characterised by severe diarrhoea with blood, can be caused by various pathogens, including *Entamoeba histolytica* (amoebic dysentery) and *Shigella* species (bacillary dysentery) (Pfeiffer et al., 2012). Both forms are transmitted through contaminated water sources and are exacerbated by poor sanitation practices (Thompson et al., 2015). Outbreaks of dysentery are often linked to informal settlements with inadequate water and sanitation facilities (Nguyen et al., 2021). Symptoms can lead to severe dehydration, particularly in vulnerable populations, highlighting the critical need for improved water quality and sanitation. Although dysentery is significant for public health, there is limited research using remote sensing for mapping outbreaks in South Africa, indicating a specific gap in geospatial methods.

2.3.6 Water-related diseases

Findings from this review have drawn our attention to malaria (Figure 2.6). Malaria is a major waterborne disease and is endemic in three provinces of South Africa: KwaZulu-Natal, Mpumalanga, and Limpopo. Malaria is transmitted by the bite of an infected *Anopheles* mosquito, which acts as a vector for *Plasmodium falciparum* (Beier et al., 1999). Although malaria is often referred to as a 'disease of poverty' (Sachs and Malaney, 2002), its transmission is significantly correlated to climatic variables, such as precipitation (Ikeda et al., 2017), temperature (Ikeda et al., 2017), relative humidity (Adeola et al., 2017), vegetation (Adeola et al., 2019; Malahlela et al., 2018), and land use/cover (Paul et al., 2018). In South Africa, incidences of malaria are either imported or locally transmitted, putting approximately 4.9 million people at risk of contracting the disease. Some of the crucial developments in southern Africa aimed at eradicating malaria in South Africa include a joint multinational cross-border project called MOSASWA, which included Mozambique, South Africa, and eSwatini due to the adjacency of malaria transmission across these countries. Both Mozambique and eSwatini border the endemic malaria provinces of South Africa, and as such, a cross-border initiative is necessary for reducing the malaria burden in these three countries and to develop an associated malaria control programme (Moonasar et al., 2016). South Africa had set the elimination target (zero local cases) by 2020 by WHO standards. However, that target has not been met, and currently, local malaria transmission continues, albeit at very low rates (Moonasar et al., 2021).

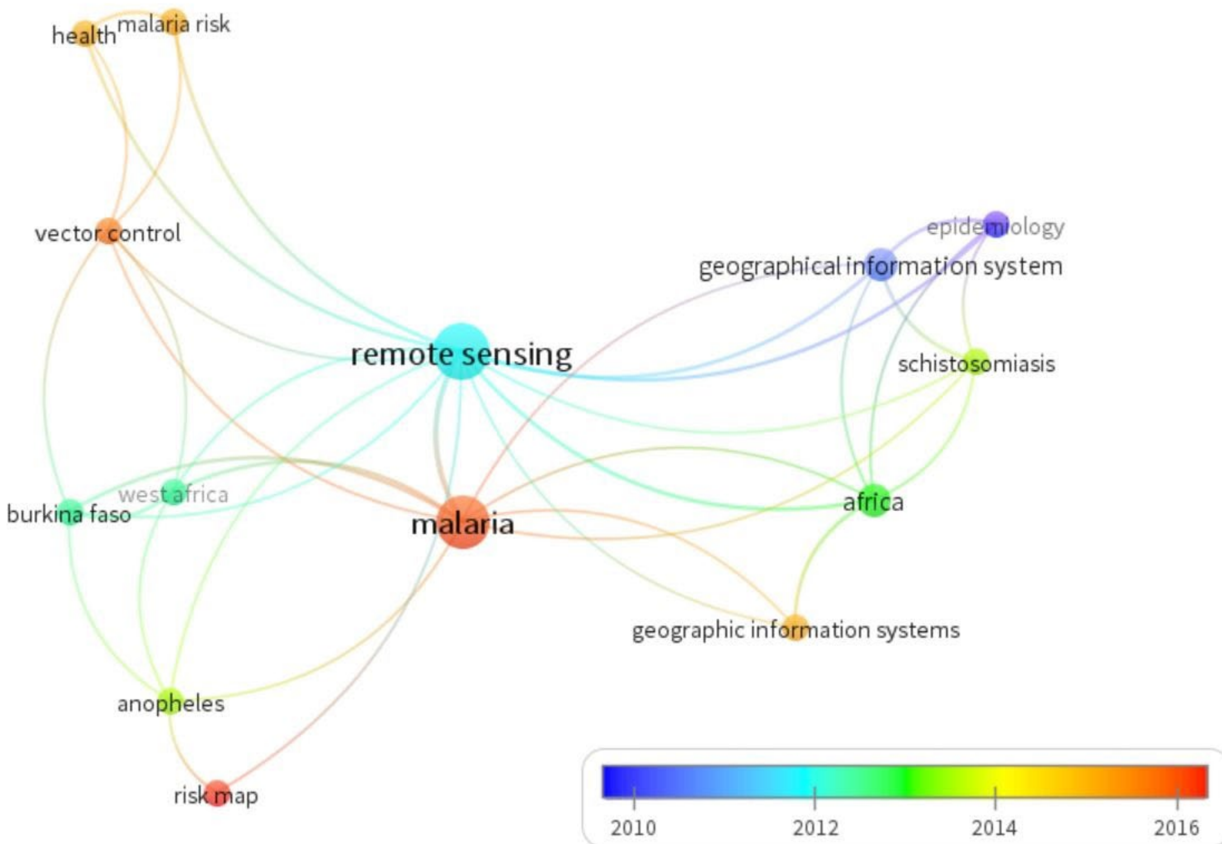

Figure 2.6. Overlay visualisation of remote sensing literature in relation to water-related diseases

The use of spatial information technology continues to support efforts aimed at eliminating malaria in southern Africa. Several studies have been conducted to this effect. In this review, we identified the first of such initiatives, the Mapping Malaria Risk in Africa project, which used GIS. In this project, climate data, malaria vector distribution, and transmission rates were used to model malaria occurrence in Africa, including South Africa (Le Sueur et al., 1997). Subsequently, Craig et al. (1999) utilised a climate model to predict the potential malaria transmission areas in sub-Saharan Africa, which later became a baseline for contemporary climate-based models for malaria prediction in South Africa (Martin et al., 2002). A few more recent studies have utilised various remote sensing variables such as the normalized difference vegetation index (NDVI), normalized difference water index (NDWI), and land surface temperature, which were directly derived from Landsat data (Adeola et al., 2019; Malahlela et al., 2018). These are areas that have little to no informal settlements but are largely rural parts of South Africa (Table 2.3). Additionally, Malahlela et al. (2019) used remote sensing techniques to map the potential breeding sites for malaria vectors (*Anopheles arabiensis* and *A. fenestus*) at a 10 m spatial resolution. Malaria distribution mapping is focused mainly on the malaria endemic areas (with low to moderate risks) found in Mpumalanga, Limpopo, and the northern parts of KwaZulu-Natal.

Table 2.3. Some of the commonly occurring research publications on the applications of remote sensing for mapping malaria in South Africa

Study area	Remote sensing data used	Analytical method	Findings	References
Vhembe district, Limpopo	Landsat 5 TM	Logistic regression modelling, image differencing	The soil-adjusted vegetation index and malaria distribution were significantly ($p < 0.05$) positively related at all buffer distances, which suggests that the malaria vector (*Anopheles arabiensis*) prefers productive and greener vegetation.	Malahlela et al. (2018)
Nkomazi municipality, Mpumalanga	Landsat 5 TM	Multi-criteria evaluation, image differencing	The resulting malaria risk map depicted that Komatieport, Malelane, Madadeni, and Tonga are prone to high malaria incidence rates.	Adeola et al. (2017)
Vhembe district	Sentinel-2 MSI	Stepwise linear regression, geo-statistics	The interpolation error for estimating cattle hoofprints/100 m^2 can be better minimised using co-kriging than with both ordinary kriging and stepwise multiple linear regression methods. Also, there are more cattle hoofprints in malaria-prone than in the malaria-free areas.	Malahlela et al. (2019)
South Africa, Swaziland (now eSwatini), Mozambique	RapidEye, Geo-Eye1, Ikonos, ASTER, MODIS	Classification, decision tree analysis, Bayesian modelling	The study successfully produced remote sensing products at high to very high spatial resolution for the study area. These products were further used for modelling malaria incidence and the analysis of environmental factors that favour vector breeding.	Franke et al. (2015)
Mpumalanga	MODIS, AVHRR	Random forest	The combination of climatic variables that produced the highest prediction accuracy was altitude, NDVI, and temperature.	Kapwata and Gebreslasie (2016)

	This suggests that these three variables have high predictive capabilities in relation to malaria transmission.

ASTER, Advanced spaceborne thermal emission and reflection radiometer; AVHRR, Advanced Very High Resolution Radiometer; MODIS, Moderate Resolution Imaging Spectroradiometer; MSI, multispectral imager; TM, Thematic Mapper

Yellow fever is an acute viral haemorrhagic disease primarily transmitted by infected *Aedes* spp. mosquitoes, with a significant prevalence in West Africa (Adam and Jassoy, 2021). If left untreated, yellow fever can result in a mortality rate of up to 50% among individuals presenting severe symptoms, and currently, no specific cure exists (Kuno, 2024).

Although not a notifiable disease, bilharzia or schistosomiasis poses a concerning public health problem in South Africa. The common species of blood flukes include *Schistosoma haematobium* and *S. mansoni,* which tend to cause intestinal and urogenital bilharzia in South Africa. It is estimated that approximately 2–3 million children are infected with bilharzia, while the population at risk of infection can be as high as 20 million people (Moodley et al., 2003). Kabuyaya et al. (2017) sought to understand the risk factors of schistosomiasis based on the infection status among rural school children in KwaZulu-Natal. In that study, it was found that approximately 37.5% of children tested positive for schistosomiasis due to their age, poor sanitation, and access to water, among other factors. In residential suburbs, the transmission of bilharzia has been documented to be possible in water bodies near or in built-up areas, which can act as transmission sites in what is known as urban bilharzia (Appleton and Miranda, 2015). Walz et al. (2015) conducted a systematic literature review to assess the utility of remote sensing in schistosomiasis risk profiling and identify challenges limiting its optimal application. Key methodologies included examining ecological and epidemiological factors influencing disease risk, analysing remote sensing data and variables used in prior studies, and synthesising the link between environmental conditions and remote sensing measures. The findings highlighted the significant, yet underutilised, potential of remote sensing for spatially explicit risk profiling. However, existing studies often fail to account for spatial gaps between snail habitats (disease transmission sites) and locations where prevalence data are collected. This underscores the need for a tailored approach, optimising remote sensing variables and scales within ecological zones to enhance targeted interventions.

Remote sensing technology holds significant promise in enhancing the understanding and control of waterborne and water-related diseases, especially in regions where the challenges of water quality, sanitation, and population density are most pronounced. Through the integration of satellite-based data and GIS, it is possible to identify environmental and climatic factors influencing disease dynamics, offering crucial insights for targeted interventions and more efficient disease control.

For diseases like cholera, which are influenced by water quality and environmental factors, remote sensing can play a pivotal role in identifying areas at risk based on the presence of key environmental conditions such as water temperature, turbidity, and phytoplankton concentrations. Despite the successful use of GIS to map cholera outbreaks historically, there remains a gap in utilising satellite imagery to track and monitor cholera outbreaks, particularly in southern Africa. The region's urbanising informal settlements, where population density often leads to heightened risks of disease transmission, present an opportunity to harness space-based technologies in real-time monitoring and early warning systems. Similarly, while the use of remote sensing in monitoring malaria transmission, particularly through mapping environmental variables, such as vegetation indices and water bodies, has been explored in parts of South Africa, there remains substantial room for innovation. Most current malaria mapping efforts focus on rural areas, with little consideration of informal settlements. Yet, these settlements often face water-related challenges, such as stagnant water, which is an ideal breeding ground for malaria vectors. Thus, there is a potential opportunity to utilise high-resolution satellite imagery to enhance malaria risk mapping in both rural and urban settings, supporting efforts to reduce transmission and guide resource allocation.

Challenges in the application of remote sensing for disease mapping include the high cost of obtaining high-resolution remote sensing data and the complexity of analysing such data for non-experts. Moreover, waterborne diseases like typhoid fever and cryptosporidiosis may not exhibit strong spectral signatures, complicating their detection from space-based platforms. Despite these challenges, the integration of remote sensing with other environmental data (e.g. hydrological models) can still provide valuable insights for disease surveillance and the development of more effective public health strategies. The under-utilisation of remote sensing in disease mapping, particularly for typhoid fever and schistosomiasis (bilharzia), highlights a key opportunity to improve spatially explicit risk profiling. While remote sensing has been used to monitor malaria vectors and schistosomiasis transmission sites, the gap in spatial data for other diseases suggests a need for further research and innovation in the application of these technologies. Tailoring remote sensing techniques to specific environmental and ecological zones could significantly improve the efficiency and accuracy of disease risk mapping and intervention strategies.

2.3.7 Recent technology (unmanned aerial vehicles)

In this review, we found the use of unmanned aerial vehicles (UAVs) for mapping and monitoring water quality or infectious waterborne and water-related diseases to be extremely limited in South Africa. This is despite the popularity of UAV technology in the scientific community because of its versatility for epidemiological applications and disease surveillance. For example, in sub-Saharan Africa and elsewhere in the world, studies have been conducted to map the conditions and distribution of vector-borne diseases such as malaria and dengue (Trujillano et al., 2023; Valdez-Delgado et al., 2023). Unmanned aerial vehicle technology is primarily used to collect detailed georeferenced spatial information on the environmental conditions and parameters that have a major influence on disease transmission and vector populations. There are several environmental factors that are directly or indirectly linked to vector-borne disease transmission, such as changes in surface temperatures, land use/cover changes, spread of the human population, and the availability of water bodies that act as breeding sites (McCann et al., 2017; Tusting et al., 2013). Chamberlin et al. (2020) demonstrated that UAVs can be used to map the potential habitats for schistosomiasis vectors. The UAV data are advantageous in that they have a higher spatial resolution than the typical remote sensing sets, such as Landsat (30 m) and Sentinel-2 (10 m), and a very short repeat cycle that can be pre-determined by the operator. In addition, UAVs are relatively inexpensive, lightweight, and versatile. Despite these advantages, the use of UAVs may yield unintended consequences to the communities affected by waterborne and water-related diseases and, therefore, present some risks to such communities. For example, the use of UAVs may result in some concerns relating to security (such as infringement of airspace regulations), privacy, noise, aesthetics, and may generate unwarranted rumours within communities.

2.3.8 Opportunities for remote sensing applications in public health

The use of UAVs enjoys some level of popularity in remote sensing for mapping of micro-water body quality and for epidemiological studies. For example, Cillero Castro et al. (2020) utilised UAV and satellite multispectral data to monitor water quality in small reservoirs in the northwestern Iberian Peninsula. The UAV data demonstrated moderate agreement with the commonly used Landsat and Sentinel-2 data for mapping eutrophication in a small water body. Wasehun et al. (2024) described the use of UAV data for mapping water quality in small bodies, including the estimation of parameters such as CDOM, TSS, TDS, and turbidity, amongst others. Adopting UAV data has gained popularity due to the high spatial resolution, minimised effects of the atmosphere due to the low altitude flights, and relatively inexpensive vehicles compared to spaceborne vehicles. Using UAV data proved effective in the identification and mapping of malaria vector breeding sites in Burkina Faso and Côte d'Ivoire, West Africa (Trujillano et al., 2023). Although there has not been substantial use of UAV data in epidemiology due to some constraints, including aerospace and flight regulatory issues, the current and future capabilities of drones could offer some benefits in enhancing efforts geared towards water quality mapping and disease monitoring.

The availability of multi-resolution geospatial datasets offers various opportunities for mapping of water quality in urban and peri-urban environments. Currently, there are numerous open-data and commercially available datasets which have the potential to improve our understanding of the spatio-temporal distributions of water quality parameters such as chl-a, water temperature (Dörnhöfer and Oppelt, 2016), CDOM, turbidity, total suspended materials, *E. coli,* and benthic vegetation (Legleiter and Hodges, 2022). Detailed assessment of these parameters is usually made possible through remote sensing data, which consider the spatio-temporal characteristics of such parameters. For instance, it is now possible to monitor the concentrations of algae/chl-a in both small and large water bodies (from ponds to lakes) thanks to satellite constellations equipped with multi-sensors that enhance the temporal resolution of data acquisition at any given point in time (Li and Roy, 2017). The availability of heritage sensors such as Landsat also offers a possibility for long-term monitoring of not only water quality parameters but also environments that may be associated with the potential habitats for waterborne disease pathogens and vectors. This invariably improves our understanding of disease outbreaks, spread, and management, which is enhanced through early detection methods, more so in developing countries with limited resources. Meanwhile, the advancement in machine learning algorithms for both classification and regression purposes and cloud computing offer an added advantage in the employment of satellite imagery in water quality mapping at larger scales and open more avenues for automated monitoring.

2.4 CONCLUSIONS

There is a growing interest in the use of remote sensing data for the assessment of public health in South Africa and around the world. Although current trends indicate dwindling water quality in water bodies close to informal settlements in South Africa, it appears that very limited remote sensing studies are conducted to document the gravity of the poor water quality situation in these areas. The limited research in informal settlements is often attributed to the unsafe nature of these environments, which are often characterised by inaccessible small water bodies, high risk of crime (potential loss of research equipment), poor infrastructure and sanitation, and narrow, undeveloped road networks. Since informal settlements often occupy very marginal land, they require very high spatial resolution remote sensing data for accurate water quality mapping, which can be considered by some as too costly an exercise to undertake. The availability of commonly used remote sensing data such as Landsat 8 or Sentinel-2 may not always provide the spatial resolution necessary for the delineation of small water bodies, and the high spatial resolution data often comes with too low a spectral resolution to detect changing levels of water quality parameters such as total coliforms or to detect the presence of *E. coli*. Unmanned aerial vehicle technology can be used as an alternative or as a supplement to satellite remote sensing due to its advantages, which include being relatively inexpensive and lightweight, producing high spatial resolution data, and offering the ability to be deployed quickly if the researcher requires it. In South Africa, the use of UAVs for mapping water quality is still relatively new, and expertise in this area needs to be developed.

The popularity of remote sensing for mapping malaria underscores the importance of this disease to decision-makers in the public healthcare domain in South Africa. This review has shown that although remote sensing has been utilised for mapping of water-related diseases such as malaria, there is still a gap, especially in the use of UAV data to map and monitor other commonly occurring waterborne and water-related diseases, such as cholera and schistosomiasis. We recommend the use of high to very high spatial resolution remote sensing data, considering that habitats and breeding sites for waterborne and water-related vectors tend to be small with ambient temperatures.

CHAPTER 3: RESEARCH METHODS

3.1 INTRODUCTION

This section discusses the methods that were employed to address the main aim of the study. It begins by describing the test sites, followed by a detailed description of the analytical methods used in this study. The analysis methods include steps undertaken to calibrate, parameterise, and validate the remote sensing-derived models. These methods were instrumental in determining the spatial distribution of parameters within the small water bodies found in the selected informal settlements.

3.2 DESCRIPTION OF THE STUDY AREA

The study was conducted in selected inland informal settlements (Mamelodi, Pretoria Gardens, Alexandra, Zandspruit and Diepsloot) found in Gauteng (26.07000° E, 28.15000° S), South Africa (Figure 3.1). The informal settlements in South Africa are mostly established out of the need to be closer to the place of work (Richards et al., 2007). The informal settlements in Mamelodi included areas such as the Eerste Fabriek (est. population = 1 300), which is part of the City of Tshwane metropolitan area—the largest municipality in Gauteng (Modiba, 2021; Nyam et al., 2024). Other informal settlements sampled in Mamelodi include Marikana, Lusaka, Phomolong, and Leeuwfontein, all of which are located along the Pienaarsrivier stream. The informal settlement of Alexandra, or 'Alex' as it is known to the locals, is located closer to Sandton City, a financial powerhouse in Africa (Masuku, 2023). Stjwetla, an informal settlement in Alex, is located along the Jukskei River and is known to experience frequent flooding (Danielak, 2022). Zandspruit and Diepsloot are the informal settlements situated at the northwestern periphery of Johannesburg. In 2014, Zandspruit comprised approximately 4 000 households (Gunter, 2014), mostly shacks and other makeshift housing. Diepsloot has approximately 13 extensions; a mixture of both formal and informal settlements whose population is estimated to be > 350 000 individuals (Sobantu and Nel, 2019; Tshililo et al., 2022). The coastal study site included the uMlazi informal settlement situated at 29.97000° E, 30.88447° S.

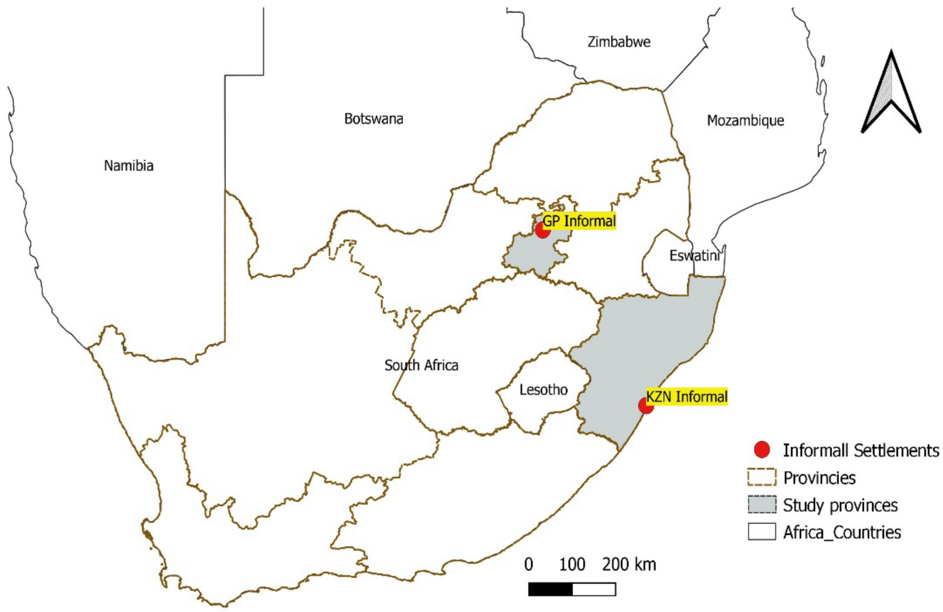

Figure 3.1. Location of the selected inland and coastal informal settlements included in the study. GP, Gauteng; KZN, KwaZulu-Natal

3.3 DATA COLLECTION

3.3.1 Field data collection

Field water sampling was conducted in August 2022 (the dry season and winter) using a random sampling method. Initially, 50 random samples were pre-allocated to five sampling sites (informal settlements) using Quantum GIS (QGIS) software (QGIS, 2022). However, only 33 samples were later collected to form the standard dataset. At each sampling point, the geographical coordinates, sample ID, and general observations of the surface water use in the locations nearby were also recorded. The collected water samples were stored in a cooler box and later sent daily to the laboratory for chemical and microbial analysis. The following aspects were assessed: pH, turbidity, EC, CDOM, chl-a, total coliforms, *Salmonella*, *E.coli*, TSS, TDS, Cd, Cu, Pb, Zn, and Fe.

For *E. coli* and coliform detection, the undiluted water samples were plated using the pour-plate technique. Specifically, 1 ml of each sample was pipetted into an empty petri dish, and 20 ml of molten Brilliance™ *E. coli*/coliform Selective Agar was added and maintained at 45°C. Subsequently, the petri dishes were gently swirled to ensure thorough amalgamation of the components and allowed to solidify. They were then incubated at 37°C for 24 h. Colonies were quantified as colony-forming units per millilitre (CFU/mL), distinguishing between purple colonies indicative of *E. coli* and pink colonies representative of other coliforms.

In instances where the undiluted samples exhibited CFU/mL values exceeding 250, further dilution steps were implemented. These dilutions included 1/10 and 1/100, after which 1 mL of the appropriately diluted sample was subjected to plating using the same technique. The newly prepared plates were then incubated at 37°C for an additional 24 h. To determine the final CFU/mL values for *E. coli* and coliforms, the colony counts were multiplied by the respective dilution factors. Prior to the detection of *Salmonella*, the samples were introduced into buffered peptone water at a ratio of 1:9 and incubated at 37°C for 24 hours. Following this incubation, 0.1 ml of the inoculated buffered peptone water was transferred to 9.9 ml of Rappaport-Vassiliadis (RV) broth, maintaining a ratio of 1:99. The RV broth was then incubated at 41.5°C, and growth was monitored using a turbidity meter.

3.3.2 Field data outlier analysis

A *Z*-score was used to detect the outliers for each variable in the standard dataset. The Z-score is defined as the statistical measurement of a score's correlation to the mean in a collection of scores (Kolbasi and Ünsal, 2015). It uses the mean and standard deviation of a given dataset (water quality parameter) as given by Equation [1]:

$$Z_i = \frac{x_i - \bar{x}}{\sigma} \qquad [1]$$

where Z_i is the *Z*-score of *i*th variable, x_i denotes the sample measurement of a given water quality parameter, and $\underline{x}$ and σ denote the mean and standard deviation of the data, respectively. A *Z*-score of zero indicates that the value is similar to the mean value, while the outliers are detected as values greater than 3 or less than –3.

3.3.3 Satellite data acquisition and pre-processing

Commercial satellite data corresponding to the field data sampling dates (11–13 August 2022) from PS were acquired. The PS data provide four spectral channels/bands in the visible to NIR spectrum as follows: blue (0.455–0.515 μm), green (0.50–0.59 μm), red (0.59–0.67 μm), and near-infrared (0.78–0.86 μm). These satellite data have a high spatial resolution of 3 m, making them very costly compared to the Landsat or Sentinel datasets. The product acquired was orthorectified for a wide variety of applications, including vegetation and water monitoring. A few selected indices were computed from the PS data to be used for subsequent regression analysis for determining water quality, and these indices are shown in Table 3.1.

Table 3.1. Selected spectral indices used in this study

Spectral index	Formula	Reference
Normalized difference water index	$\mathrm{NDWI} = \frac{(\mathrm{R_{green}} - \mathrm{R_{NIR}})}{(\mathrm{R_{green}} + \mathrm{R_{NIR}})}$	McFeeters (1996)
Normalized difference vegetation index	$\mathrm{NDVI} = \frac{(\mathrm{R_{NIR}} - \mathrm{R_{Red}})}{(\mathrm{R_{NIR}} + \mathrm{R_{Red}})}$	Deering (1978)
Blue-green index	$\mathrm{Bg} = \mathrm{R_{blue}} \times \mathrm{R_{green}}$	Ha et al. (2017)
Blue-red index	$\mathrm{Br} = \mathrm{R_{blue}} \times \mathrm{R_{red}}$	Ha et al. (2017)
Green-red index	$\mathrm{Gr} = \mathrm{R_{green}} \times \mathrm{R_{red}}$	Oliviera et al. (2016)
Red-near-infrared index	$\mathrm{Rn} = \mathrm{R_{red}} \times \mathrm{R_{NIR}}$	Gilerson et al. (2010)

3.4 DATA ANALYSIS

Figure 3.2 shows the summary of the workflow developed for the data analysis. The analytical method is divided into three sub-sections, as follows: (i) water body extraction, (ii) correlation analysis, and (iii) water quality mapping.

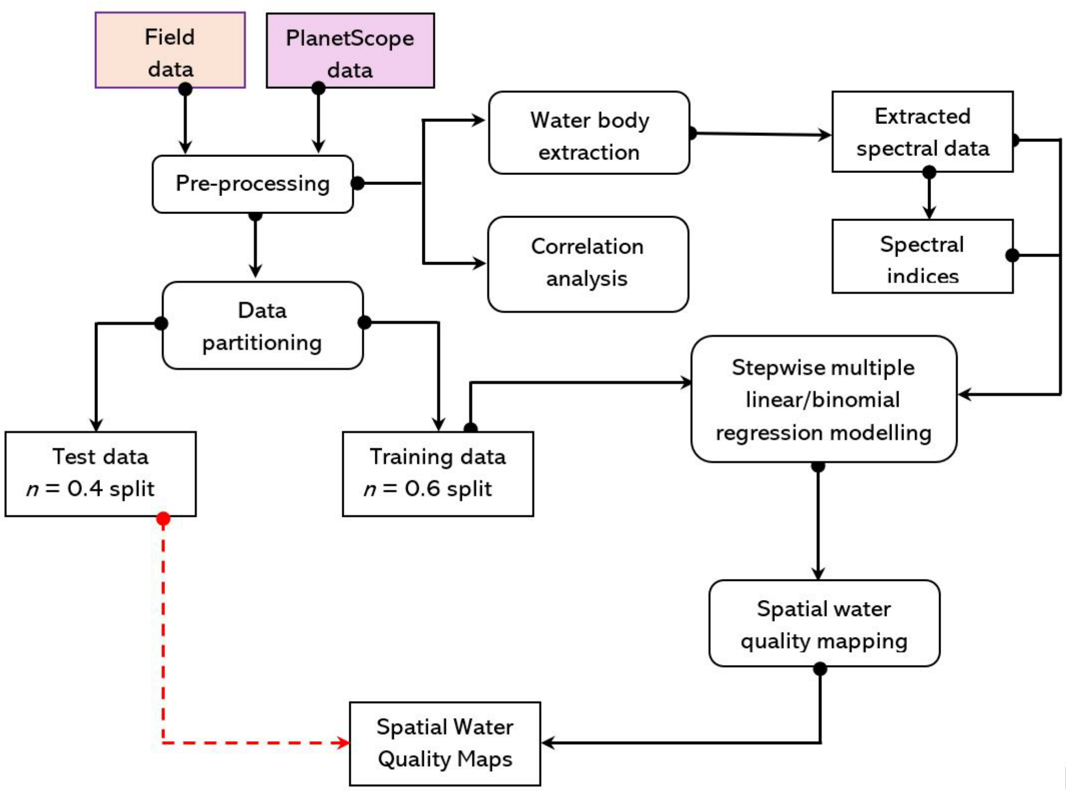

Figure 3.2. Research workflow adopted in this study

3.4.1 Water body extraction

Extraction of small to micro water bodies served as the basis for subsequent analytical methods involved in this research. The maximum likelihood classification was undertaken for the extraction of the water body thematic layer from the PS data. The maximum likelihood classifier (MLC) is a supervised parametric algorithm that describes each band by the normal distribution (Basheer et al., 2022; Norovsuren et al., 2019). The MLC was performed in QGIS software (version 3.32.1) using the semi-automatic classification plugin (Congedo, 2021). A total of four land use/cover classes were selected, including water, bare surfaces, built-up areas, and vegetation. In order to calibrate and adjust the hyperparameters of the classification model, 64 training samples (4651 pixels) were used, while 42 samples (3108 pixels) were used for testing the accuracy of the training model. Using the final classified image, we extracted the water class, separated it from other land cover types, and converted it into a vector layer to subset spectral information from the PS data.

3.4.2 Statistical analysis

The water quality parameters (field data) were statistically analysed using one-way analyses of variance (ANOVAs) across the five informal settlements. The one-way ANOVA is one of the commonly used statistical approaches that compares the means of three or more groups, and has been applied elsewhere for water quality mapping (Hassan et al., 2024). Additionally, Tukey's Honestly Significant Difference test was performed in R (R Core Team, 2024) to establish the significant differences in water quality parameters across five informal settlements.

3.4.3 Water quality indexing

The weighted arithmetic water quality index (WAWQI) method classified the water quality according to the degree of purity using water quality parameters of interest (Brown et al., 1972). Equation [2] was used to calculate the WAWQI for the three locations under study (i.e. Tshwane, Ekurhuleni and the West Rand municipalities).

$$\mathrm{WAWQI} = \frac{\sum \mathrm{Q_i W_i}}{\sum \mathrm{W_i}} \qquad [2]$$

Where Q_i is the sub-index of the *ith* parameter and is calculated using Equation [3].

$$Q_i = \left(\frac{V_i - V_0}{S_i - V_0}\right) \qquad [3]$$

where V_i is the estimated concentration of the *ith* parameter in the analysed water, V_0 is the ideal value of this parameter (ideal value is '0' for all parameters except for pH = 7.0 and DO = 14.6 mg/l) and S_i is the recommended standard value of the *ith* parameter (WHO, 2017; DWAF, 1996). The unit weight (W_i) for each of the water quality parameters is calculated using Equation [4].

$$W_i = \frac{K}{S_i} \quad [4]$$

K is the proportionality constant, which is calculated using Equation [5].

$$K = 1 \sum \frac{1}{S_i} \quad [5]$$

The WAWQI results were compared with the SAWQG for (i) Agricultural use: Irrigation and (ii) Recreational standards. This was done assuming that the community members are less likely to use the water for drinking, and thus the drinking-water quality standard was abandoned in favour of the two standards mentioned above. Table 3.2 shows the WAWQI score range and probable usage aligned to each range.

Table 3.2. Water quality index (WQI) range, status, and possible usage of water (Brown et al., 1972)

WQI range	Water quality status (WQS)	Probable usage
0–25	Excellent	Drinking, irrigation, and industrial purpose
26–50	Good	Drinking, irrigation, and industrial purpose
51–75	Poor	Irrigation and industrial purpose
76–100	Very poor	For irrigation purpose
> 100	Unsuitable for drinking purpose	Proper treatment required before any kind of usage

3.4.4 Mapping potential and actual water bodies

Water bodies were mapped by employing the PS data and the image classification technique. The techniques employed for the assessment of potential water bodies include the use of the digital elevation model data derived from the Advanced Land Observing Satellite (ALOS) Phased Array type L-band Synthetic Aperture Radar (PALSAR) data. The ALOS PALSAR data were downloaded with a spatial resolution of 12.5 m. The PALSAR was developed by the Japanese Ministry of Economy, Trade, and Industry and the Japan Aerospace Exploration Agency for the acquisition of data beneficial to resource exploration and environmental protection. The data were obtained from the Alaska Satellite Facility site (https://search.asf.alaska.edu/#/). The triangulated irregular network and the multiple linear model were used to map the potential water bodies using QGIS software.

3.4.5 Validation

In order to test the reliability and accuracy of the predictive models, independent test data were used in each of the modelling stages with the PS data. Overall, producer and user accuracies and the kappa coefficient were used to derive the surface water bodies using the pixel-based MLC. The overall accuracy is the statistical metric that seeks to quantify the overall proportion of correctly classified pixels to the total number of pixels in an image. The producer accuracy is defined as the reference-based accuracy assessment computed by reviewing the predictions produced for a class and by establishing the percentage of correct predictions. The user's accuracy is a map-based accuracy computed by reviewing the reference data for a class and establishing the percentage of correct predictions for these samples (Bogoliubova and Tymków, 2014). The kappa coefficient is a non-parametric measure of the agreement between the predicted/classified and reference pixels. The root mean square error (RMSE) and the MAD were used for assessing the accuracy of the predicted water quality values resulting from the stepwise multiple linear regression model. The RMSE is given by Equation [6].

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(\hat{y}_i - y_i)^2}{n}} \qquad [6]$$

where n is the number of observations, $\hat{y}_i$ represents the predicted values, and y_i represents the observed values. The MAD is given by Equation [7] as follows:

$$\mathrm{MAD} = \sum_{i=1}^{n} \frac{(\hat{y}_i - y_i)^2}{n} \qquad [7]$$

In the case of *Salmonella* distribution, using D^2, which is similar to R^2, is recommended. The final model goodness of fit was measured by the deviance (D^2), which is analogous to the coefficient of determination (R^2) peculiar to the logistic regression model (Rossiter and Loza, 2012). The D^2 is given by Equation [8].

$$D^2 = 1 - \left(\frac{Residual\ deviance}{Null\ deviance}\right) \qquad [8]$$

CHAPTER 4: RESULTS AND DISCUSSION[2,3]

4.1 REMOTE SENSING TECHNIQUES FOR WATER QUALITY MAPPING: INLAND

The outlier analysis revealed the existence of a relatively high number of sample outliers (67%) in the informal settlement of Zandspruit (Table 4.1). Overall, approximately 12% of the samples (n = 4) contained outliers and were removed from the analysis of individual indicators.

Table 4.1. Outlier analysis for samples in four informal settlements

Informal settlement	TSS	CDOM	Chl-a	Cd	Cu	Zn
Zandspruit	1	0	1	0	1	1
Mamelodi and surrounding area	0	0	0	1	0	0
Alexandra	0	0	0	0	0	0
Diepsloot	0	1	0	0	0	0
Pretoria Gardens	0	0	0	0	0	0
Total	1	1	1	1	1	1

CDOM, coloured dissolved organic matter; chl-a, chlorophyll-a; TSS, total suspended solids

4.1.1 Correlation analysis

Figure 4.1 shows the correlations between the remote sensing data and various water quality indicators. The correlations between remote sensing data and water quality indicators were mostly weak, with the strongest correlation occurring between PS spectral band 1 (blue) and turbidity (r = 0.61). The weakest and probably insignificant correlations were found between *Salmonella* presence/absence and band 1 (0.01) and band 3 (0.01). Additionally, the correlations between the PS data and heavy metals were relatively weak, with the strongest correlation occurring between Cu and the NIR band (r = 0.38). The heavy metals were generally negatively correlated with the remotely sensed data (Figure 4.2).

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[2] Based on the published article as follows: MALAHLELA OE, HLENGWA N, MOTHAPO MC and MATHIVHA FI (2026) Exploring the Capability of High Spatial Resolution PlanetScope Data for Mapping Water Quality in Informal Settlements: A Case Study of Selected Informal Settlements in Gauteng, South Africa. *Applied Geomatics* **18**: 49. https://doi.org/10.1007/s12518-026-00693-3.

[3] Based on the published article as follows: HLENGWA N, MALAHLELA OE, MOTHAPO MC and MATHIVHA FI (2025) The analysis of water quality in the informal settlements of Gauteng province in South Africa. *Discover Water* **5** 35 (2025). https://doi.org/10.1007/s43832-025-00223-z.

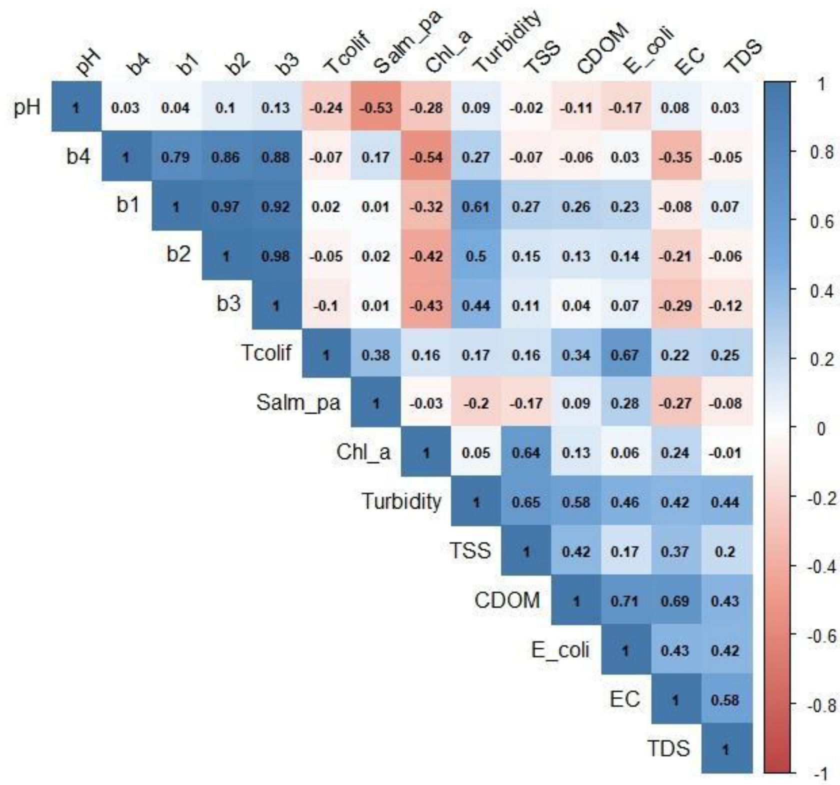

Figure 4.1. Correlation (*rho*) plot of various biogeophysical water quality indicators and the PlanetScope data. CDOM, coloured dissolved organic matter; chl-a, chlorophyll-a; EC, electrical conductivity; Salm-pa, Salmonella presence/absence; Tcolif, total coliform concentration; TDS, total dissolved solids; TSS, total soluble solids

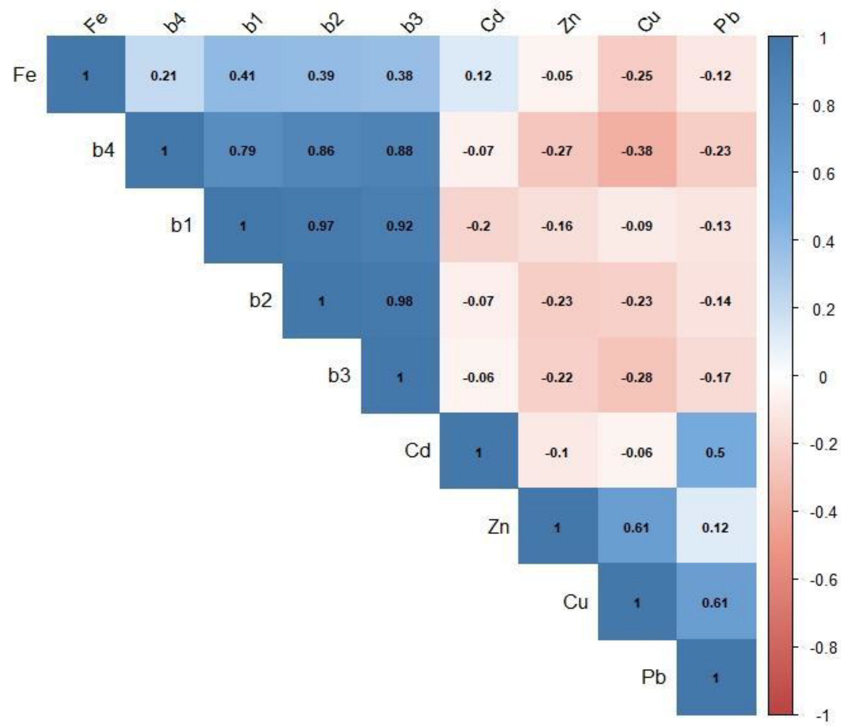

Figure 4.2. Correlation plot between the PlanetScope data and heavy metals.

4.1.2 Image classification

The results of image classification reveal that the MLC was able to yield an overall accuracy of 0.90 (90.2%) and a kappa coefficient of 0.85. The built-up areas class had the highest producer accuracy (100%) while the bare areas class yielded higher user accuracy (100%) than any other land use/cover classes (Table 4.2).

Table 4.2. Confusion matrix for land use/cover classification

	Water	**Vegetation**	**Built-up**	**Bare areas**	**Total**
Water	143	67	0	0	210
Vegetation	91	378	9	0	478
Built-up	0	41	2115	97	2253
Bare areas	0	0	0	167	167
Total	234	486	2124	264	3108
Kappa	**0.85**				
Overall accuracy	**0.90**				
Producer accuracy	0.61	0.78	1.00	0.63	

User accuracy	0.68	0.79	0.94	1.00

4.1.3 Water body extraction

The water bodies class was then extracted from the results of the classification, and Figure 4.3 (*a*) and (*b*) show the subset of extracted water bodies and the MLC land use/cover classes selected. The extracted water bodies allowed for the targeted water quality analysis in line with the field data collection.

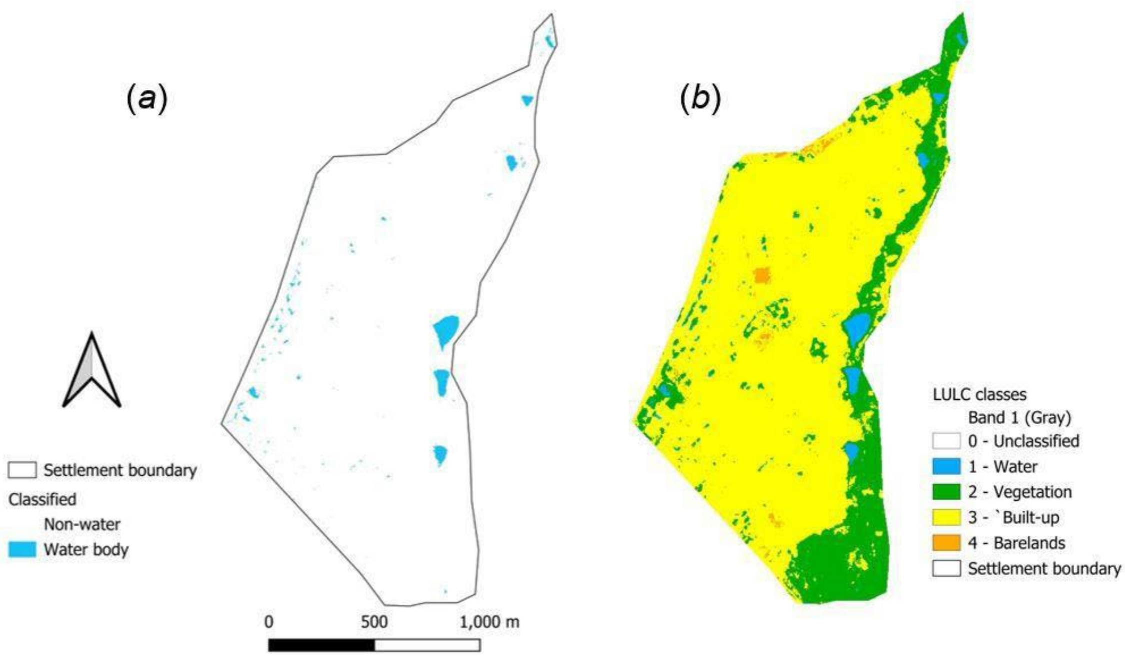

Figure 4.3. The result of water body extraction (a) and the land use/cover classification (b) derived from the PlanetScope data

As expected, the result of the image classification through MLC proved to be reliable, with an overall accuracy of 90%. This finding agrees with findings made by Otukei and Blaschke (2010), who concluded that the MLC is capable of deriving acceptable classification accuracy (> 85%) similar to the non-parametric classifiers. Due to the inherent nature of informal settlements, such as very densely populated building structures per unit area, it is not surprising that the PS data are capable of accurately mapping the built-up areas class in addition to the other classes. Detecting the water body class was successful in this study, permitting the subsequent analytical processes for mapping surface water quality. The largest water bodies were found to be in Tshwane (29 078 m^2), while the smallest water bodies were distributed across all informal settlements (Figure 4.4).

There were, however, linearly distributed micro water bodies (< 9 m^2), which could be a result of a misclassification due to the influence of shadows and top-water vegetation in some settlements. This is true since shadows are known to cause spectral confusion with water bodies (Schmitt, 2020). This thus reduces the capability of the parametric classifier to accurately map all the small water bodies present in a given area. Despite this, the results of water body extraction were used for subsequent analysis of water quality.

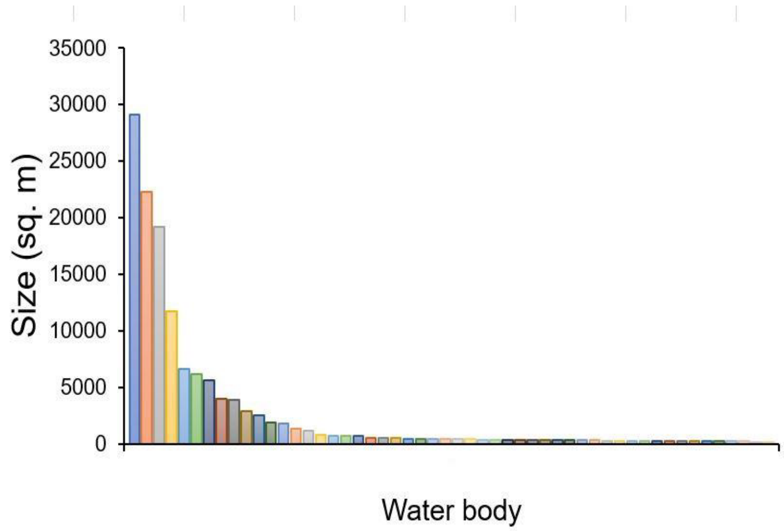

Figure 4.4. Extracted sizes of individual water bodies derived from the PlanetScope data

4.1.4 Water quality mapping

Various stepwise linear regression models were m^{2}produced for all water quality parameters except for *Salmonella*, which required logistic regression models due to the nature of the response variable (dichotomous response variable). Table 4.3 shows the model parameters for each model.

Table 4.3. Summary of the final model calibrated and used for prediction, and the respective validation measures from the test data

Indicator	**R^2(D^2)**	***P*-value**	**RSME**	**MAD**
pH	0.43	0.10	0.28	0.17
Electrical conductivity	0.77	0.07	13.43	7.75
Turbidity	0.71	**0.00**	17.24	8.06
Total dissolved solids	0.85	**0.02**	63.04	38.85
Total suspended solids	0.86	**0.01**	58.12	30.94
Coloured dissolved organic matter	0.51	0.42	1.88	0.98
Chlorophyll-a	0.75	**0.04**	10.29	6.91
E. coli	0.60	**0.01**	154.24	78.80
Total coliforms	0.52	0.08	385.02	231.61

Salmonella	(0.62) *		-	-
Cd	0.70	0.09	0.01	0.01
Cu	0.71	**0.03**	0.01	0.00
Fe	0.70	0.19	0.00	0.00
Pb	0.41	0.21	0.03	0.02
Zn	0.80	**0.00**	0.06	0.03

MAD, mean absolute deviation; RSME, root mean square error

Among the physical water quality parameters, the turbidity, TDS, and TSS models were significant. Moreover, only the chl-*a* and *E. coli* models were significant ($p < 0.05$) among the biochemical parameters, and only Cu and Zn were significant in the heavy metals category. The spatial modelling of water quality is shown in Figures 4.9 (a–e). In these figures, the cold colours indicate low concentrations of a given water quality indicator, while the hot colours signify high concentrations of a given water quality indicator.

All of the categories of water quality indicators (biophysical, microbial and heavy metals parameters) were successfully mapped using the PS dataset, thus demonstrating the capability of this sensor. The stepwise linear regression modelling revealed that the contribution of high spatial resolution PS data is statistically significant for mapping turbidity, TDS, TSS, chl-*a*, *E. coli*, Cu and Zn ($p < 0.05$). The mapping of parameters such as pH, TSS, CDOM, and chl-*a* has been extensively studied, while various remotely sensed datasets have been tested to quantify these indicators (Huang et al., 2023; Li et al., 2023). In this study, however, the estimation of parameters such as pH, EC, CDOM, total coliforms, *Salmonella* and the heavy metals such as Pb, Cu, and Fe was not significantly correlated with the measured quantities found in the water bodies close to the informal settlements in Gauteng. This could be attributed to the limited number of samples collected and the number of spectral bands, which is often a limitation to detailed quantification of water quality estimation (Modiegi et al., 2020). Sharaf El Din et al (2017) utilised Landsat spectral variables to map both pH and EC using an artificial intelligence framework, where an R^2 of > 0.87 was achieved for both indicators. In our study, the pH and EC models, for example, yielded an R^2 of 0.43 and 0.77, respectively, thus differing substantially from the results Sharaf El Din et al (2017) and Avdan et al (2019). The weaker pH model correlation could be attributed to the weak correlations between *in-situ* pH measurements and the four-band PS data. An improved band configuration, such as the inclusion of red-edge and shortwave infrared bands, could potentially improve the estimation of not only pH in small water bodies but also other important parameters (Ford and Vodacek, 2020). Turbidity, TDS, and TSS models were significant, thus demonstrating the utility of PS data for mapping water quality in small water bodies (Figure 4.5).

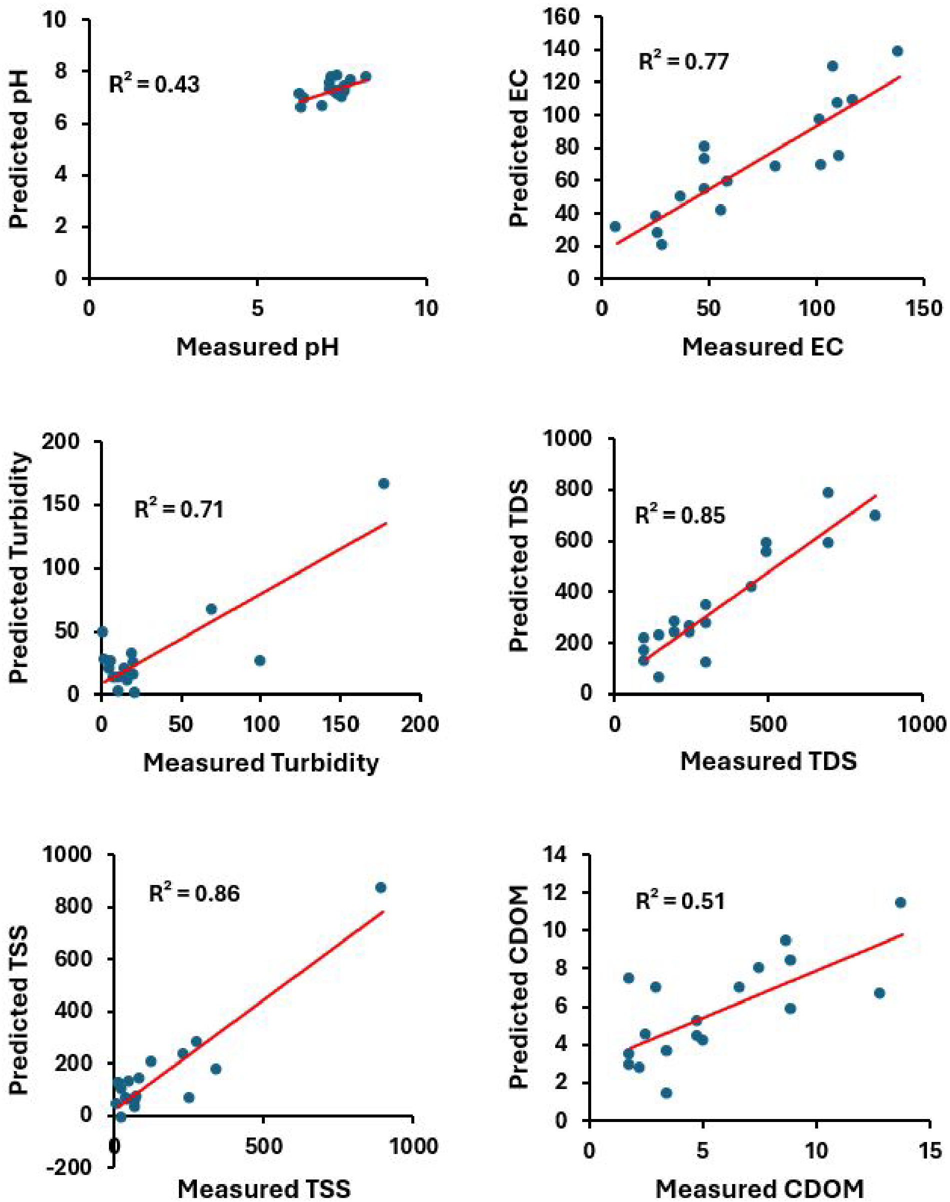

Figure 4.5. Measured and predicted water quality parameters through PlanetScope data-derived models. CDOM, coloured dissolved organic matter; EC, electrical conductivity; TDS, total dissolved solids; TSS, total suspended solids

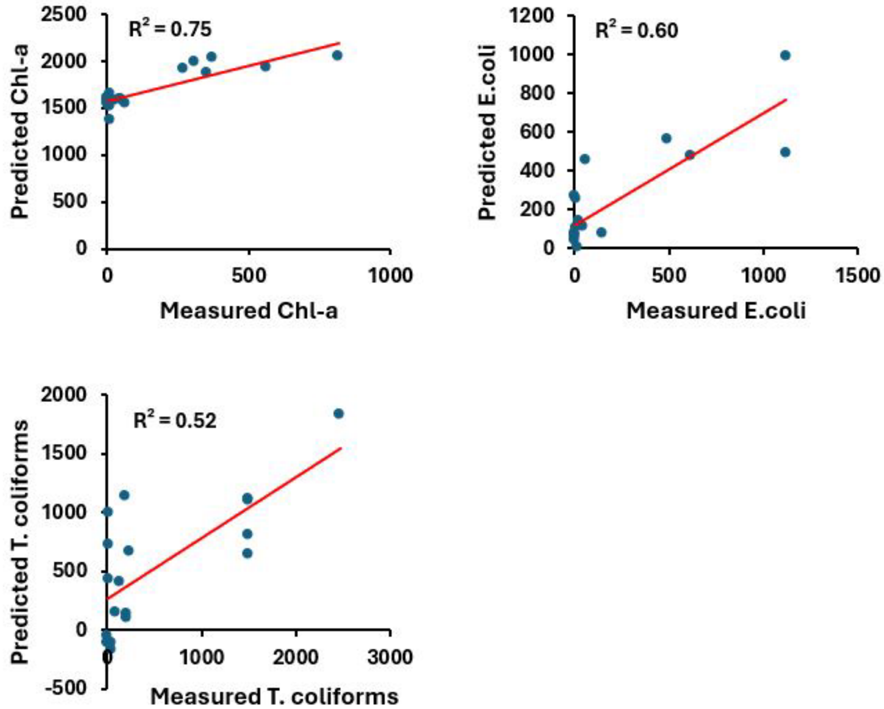

Figure 4.6. Measured and predicted biochemical and microbial water quality parameters at the selected informal settlements in Gauteng. Chl-*a*, chlorophyll-*a*; T. coliforms, total coliforms

Only models for estimating *E.coli* and chl-*a* were significant among the biochemical and microbial water quality parameters. The fairly strong positive correlation between the measured and the predicted *E. coli* population (Figure 4.6) suggests that the PS dataset can potentially be used as a tool for mapping and monitoring this microbial water quality parameter. The results, however, yielded relatively lower R^2 values than those of Hong et al. (2024) and Morgan et al. (2021), whose studies obtained an R^2 of 0.77 and 0.94, respectively. Conversely, the chl-*a* model calibrated for the informal settlement micro water bodies yielded significant and positive correlations between measured and predicted concentrations (R^2 = 0.75). In part, the significant correlations obtained in this study may be attributed to the complexities of the micro water bodies measured, especially because these water bodies are located in areas that are tens of kilometres apart from each other in different informal settlements (Figure 4.6). The higher *E. coli* concentrations, for example, are often associated with water bodies in close proximity to informal settlements in South Africa (Morole et al., 2021). Modelled *E. coli* concentrations were higher for the Alexandra informal settlement than for the other settlements in the study area.

The predicted levels of Cu and Zn were significantly correlated with the measured concentrations. However, the R^2 obtained for most metals were > 0.70, with the exception of Pb, which yielded an R^2 of 0.40 (RMSE = 0.03, MAD = 0.02). This signifies the importance of PS spectral data in estimating heavy metals in informal settlement water bodies. Figure 4.7 shows the correlations between measured and predicted values of heavy metals using only the PS data. Only two models used to map heavy metals were significant. This could be attributed to the data used (broadband multispectral data) since previous studies have shown that metal sensitivity is better detected using hyperspectral remote sensing data (Choe et al., 2008). Figure 4.10 shows the spatial distribution of Zn across all the informal settlements. Generally, the higher concentrations of Zn are found at the shallow side of the water bodies, while the deeper parts of the water bodies tend to have lower Zn levels.

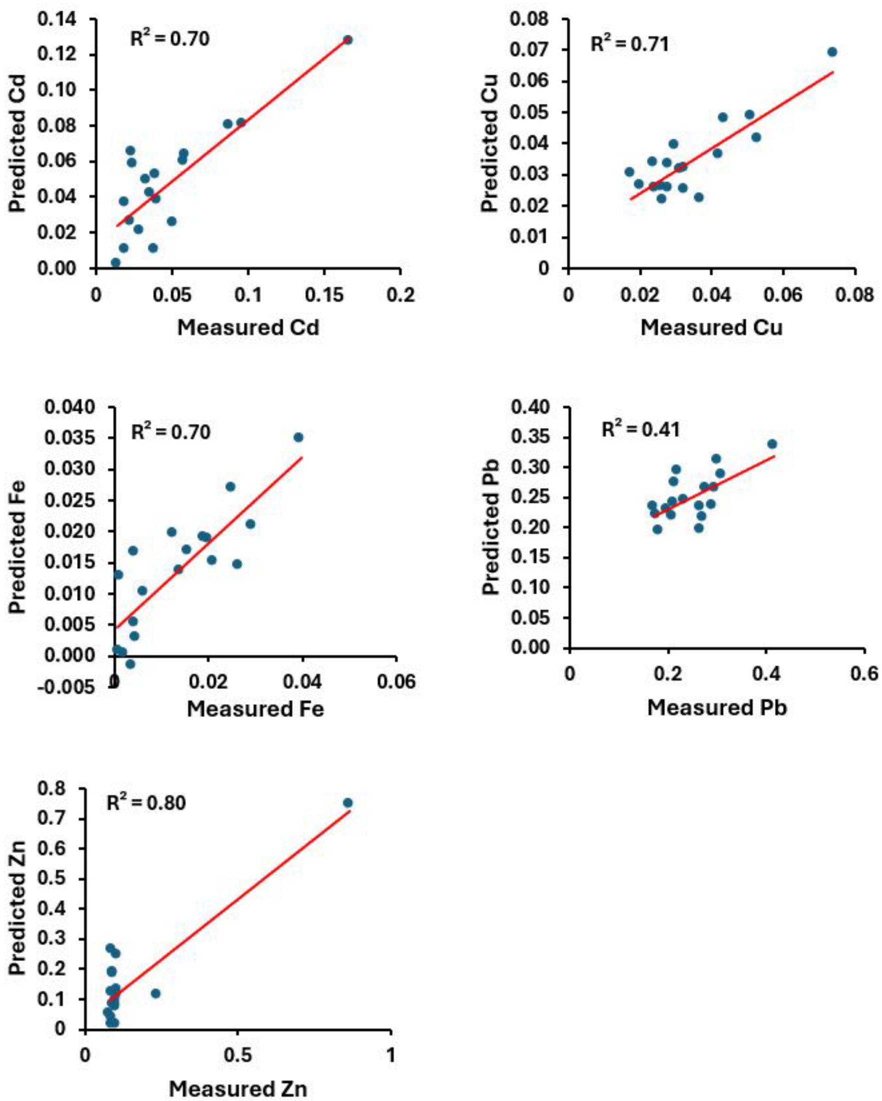

Figure 4.7. Predicted and measured heavy metals in the study area

The limited number of spectral bands (*n* = 4) posed a limitation to the accuracy of the results obtained, making it impractical to derive spectral indices that rely on more sensitive spectral bands such as the shortwave infrared and the red edge. This is particularly significant because accurate water quality analysis in water bodies found in informal settlements often requires detailed information on both the apparent and inherent optical properties of the surface water at each site (Budhiman et al., 2012; Huang et al., 2023).

4.1.5 Water quality index

The WAWQI revealed that the water quality of the sampled areas varies greatly. Relatively higher WAWQI values were found across the first 12 sampling locations (sites A1 to I1) in the north of Gauteng, while lower values were obtained for the southern part of Gauteng (sites M1 to X4), as shown in Figure 4.8. Although the northern parts of Gauteng showed higher ranges, the water was within the acceptable WQI range. Table 4.4 summarises the analytical results obtained through the incorporation of the WAWQI using the entire sample dataset. The highest WQI value of 13.11 shows that the water is of acceptable quality and may be used for a number of activities (i.e., domestic use, agricultural, and industrial use), as outlined in the WAWQI range suggested by Brown et al. (1972).

Table 4.4. Descriptive statistics of the weighted arithmetic water quality index calculated

Statistic	Value
N	31
Mean	1.70
Standard deviation	2.60
Minimum	0.02
Maximum	13.11
Variance	6.74

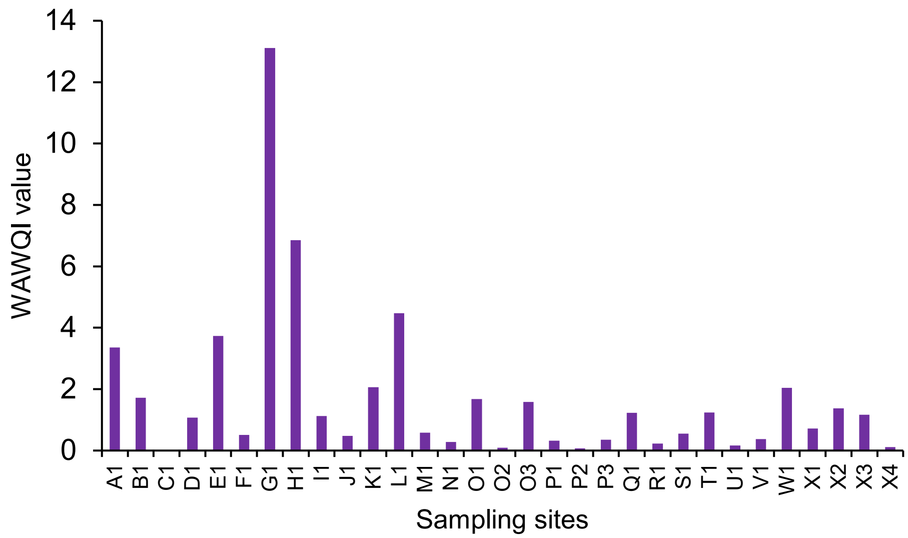

Figure 4.8. The weighted arithmetic water quality index (WAWQI) computed for all sampled areas in Gauteng province from north to south (left to right)

4.2 ANALYSING WATER QUALITY PARAMETERS IN SMALL WATER BODIES

4.2.1 Microbial detection

4.2.1.1 Chlorophyll-a

Figure 4.10 presents the distribution of chl-a. Elevated chl-a concentrations were observed at Zandspruit. However, the sites did not differ significantly. All sites demonstrated a severe condition, showing very deep discolouration and readings of > 30 ug/L. Chlorophyll-a concentration is a key indicator of water quality and is commonly used to assess ecological health, particularly concerning algal blooms. Elevated chl-a levels often signal excess nutrients, which can trigger harmful algal blooms that produce cyanotoxins harmful to both human health and aquatic life. These toxins can cause gastrointestinal, liver, and neurological issues in humans and disrupt aquatic ecosystems by depleting oxygen levels, leading to fish deaths. Earth observation technologies can monitor chl-a levels to detect potential algal blooms, helping to protect both aquatic ecosystems and human health.

4.2.1.2 Escherichia coli

The highest concentrations of *E. coli* were recorded at Diepsloot (R1, S1, and T1), significantly exceeding the recommended standards. According to the SAWQG, *E. coli* levels should not surpass 0 CFU/100 mL for irrigation purposes and should range between 0–130 CFU/100 mL for recreational use (DWAF, 1996). Site X1 had the lowest average at just under 100 CFU/100 mL.

In contrast, R1, S1, and T1 had the highest averages, reaching 1800 CFU/100 mL, which is drastically above the acceptable threshold. Diepsloot exhibited significantly higher levels of *E. coli* than the other informal settlements (Pretoria Gardens, Mamelodi, Alexandra, and Zandspruit; $p < 0.001$; Figure 4.9 and Table 4.4). This elevated *E. coli* count likely results from inadequate wastewater management, poor sanitation practices, and improper waste disposal, posing a significant risk to public health and the environment.

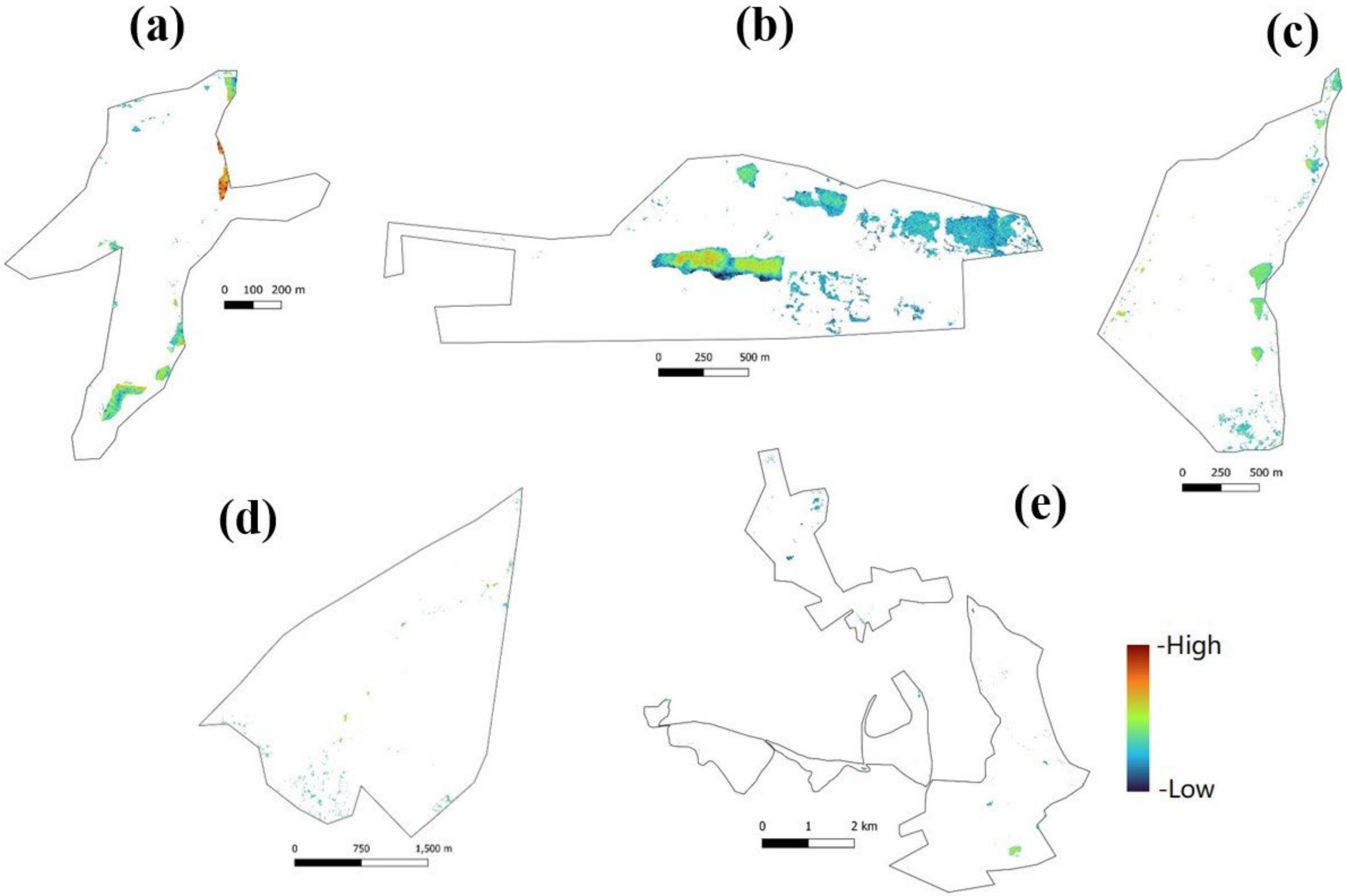

Figure 4.9. The estimated *E. coli* distribution in the water bodies of (a) Alexandra, (b) Pretoria Gardens, (c) Zandspruit, (d) Diepsloot, and (e) Mamelodi. The micro water bodies are usually so small that in some informal settlements, they appear negligible at the current spatial scale.

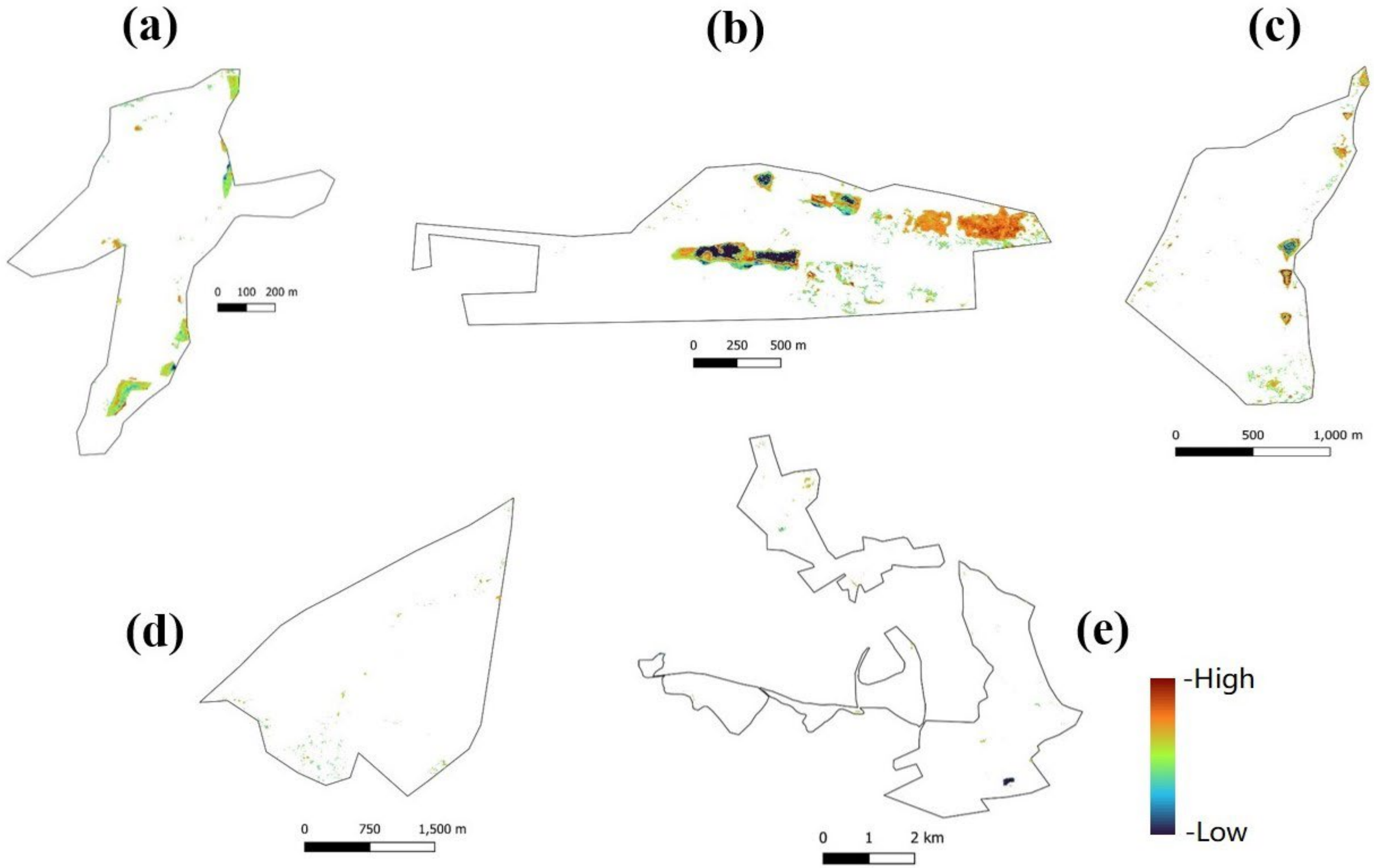

Figure 4.10. The estimated Zn distribution in the water bodies of (a) Alexandra, (b) Pretoria Gardens, (c) Zandspruit, (d) Diepsloot, and (e) Mamelodi. The micro water bodies are usually so small that in some informal settlements, they appear negligible at the current spatial scale.

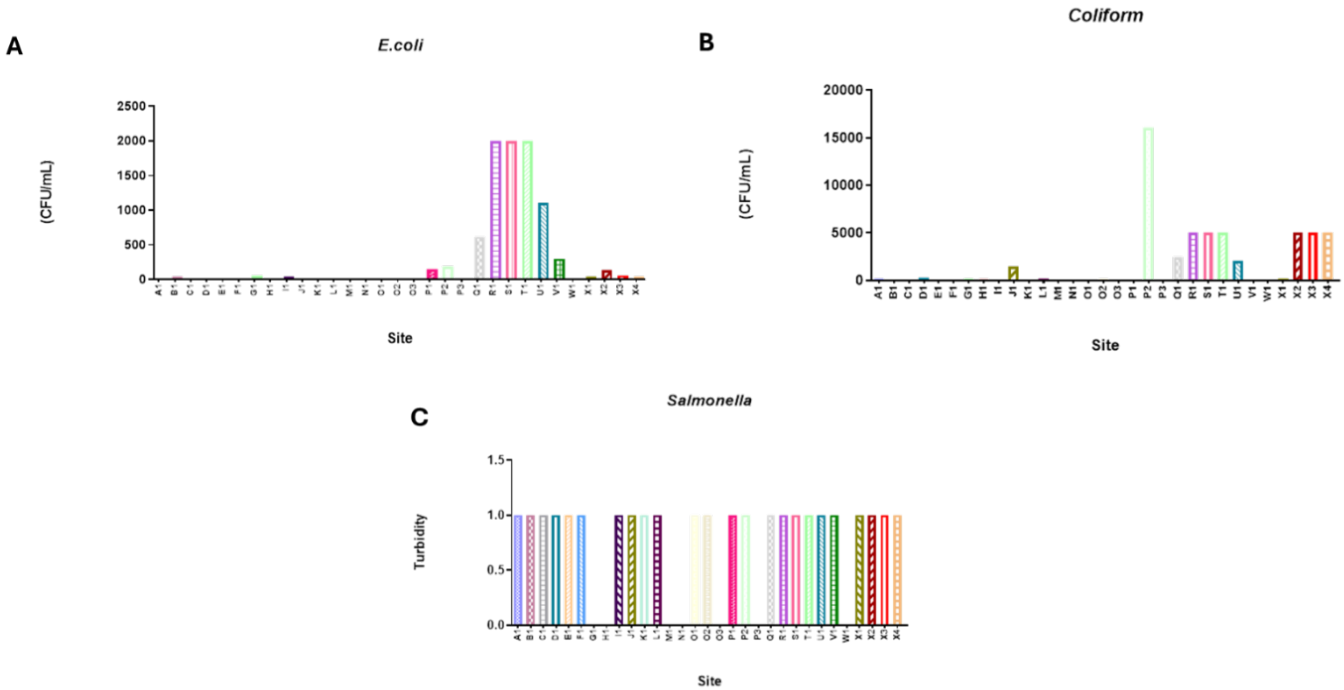

Figure 4.11. Field concentrations of contaminants in the sampled areas

4.2.1.3 Coliforms

The total coliform detection was confirmed at sites Mamelodi (J1), Zandspruit (P2, Q1), Diepsloot (R1, S1, T1, U1), and Alexandra (X1, X2, X3, and X4). However, coliform concentrations did not vary significantly across the informal settlements (Figures 4.11 and 4.12). This variability underscores the impact of environmental conditions on coliform distribution. Although faecal coliforms are not typically pathogenic themselves, they are considered indicator organisms, signalling the possible presence of other harmful bacteria (Chikodzi et al, 2017). Coliform bacteria reproduce by forming colonies, and their presence in water can be measured by counting these colonies (Murphy, 2007). According to Murphy (2007), the presence of more than 200 coliform colonies per 100 mL of water is a strong indication of pathogenic contamination. In this study, sites in Mamelodi (J1), Zandspruit (P2), Diepsloot (R1, S1, T1, U1), and Alexandra (X2, X3, and X4) exhibited high concentrations of coliform bacteria, suggesting faecal contamination and a potential risk of pathogenic organisms in the water.

4.2.2 Heavy metal detection

4.2.2.1 Lead and copper contamination

Figures 4.13 and 4.14 depict heavy metal concentrations across the sampled sites. Elevated Pb levels were notably detected at sites in Mamelodi (G1, H1) and Diepsloot (Q1 and T1). However, Pb levels did not differ significantly between the informal settlements. The Pb detected can be attributed to industrial run-off and leaching from infrastructure. High Pb concentrations pose serious health risks, including developmental and neurological effects, highlighting the need for targeted interventions.

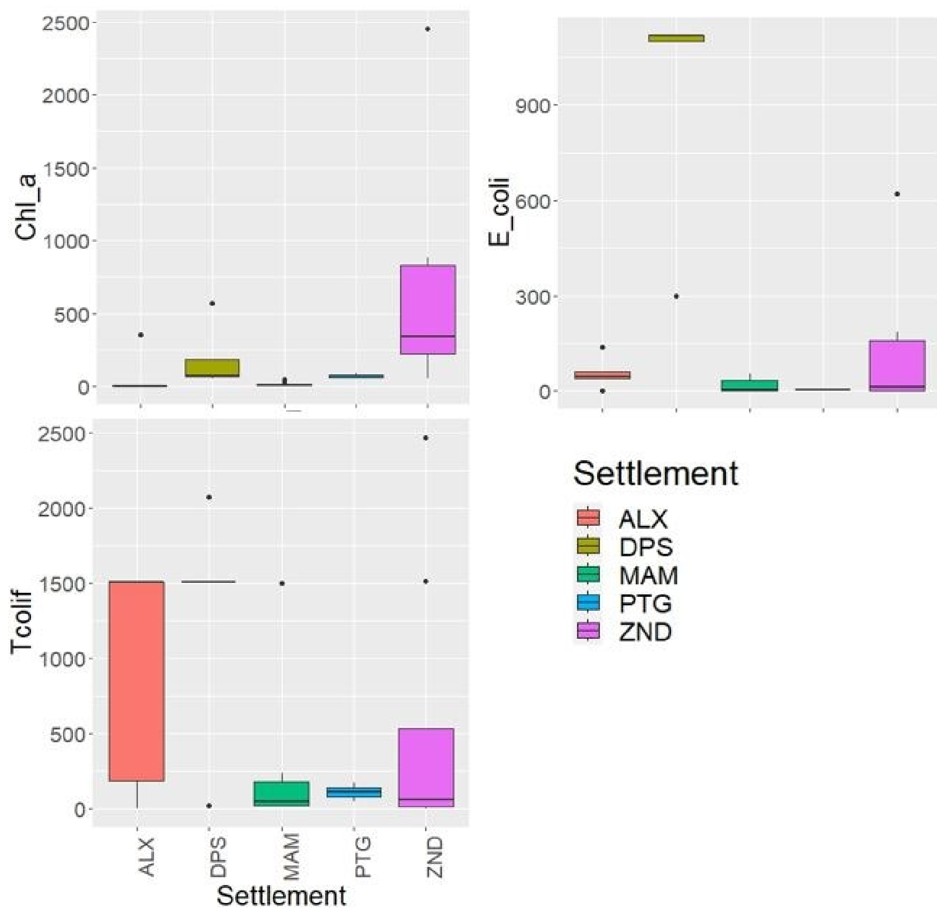

Figure 4.12. A box plot of chlorophyll-a, *E. coli*, and total coliform concentrations in water samples collected from various small bodies. ALX, Alexandra; Chl-a, chlorophyll-a; DPS, Diepsloot; E_coli, *E. coli*; MAM, Mamelodi; PTG, Pretoria gardens; Tcolif, total coliforms; ZND, Zandspruit

Copper concentrations were elevated at sites in Zandspruit (Q1) and Diepsloot (R1 and T1). However, there were no significant differences in Cu levels between the informal settlements. The detected Cu concentrations can be a result of pollution that is primarily linked to coal or wood burning in informal settlements and accumulation in sewage systems. Excessive Cu in drinking water can lead to gastrointestinal and hepatic damage, necessitating environmental quality management.

4.2.2.2 Iron, cadmium, and zinc contamination

High Fe concentrations were recorded at Mamelodi (G1and K1) and Zandspruit (N1), with the highest at Diepsloot (T1). However, there were no significant differences between the informal settlements in terms of Fe concentrations. Elevated Fe levels, often from natural sources, can cause gastrointestinal distress and liver damage. Proper management of Fe levels is essential for maintaining water quality and public health.

Cadmium levels were elevated at sites in Mamelodi (A1, G1 and H1) and Pretoria Gardens (L1). The highest concentration was found at site G1 in Mamelodi. However, Cd levels did not differ significantly between the informal settlements (Figure 4.13). Cadmium, stemming from sources such as batteries and agricultural run-off, poses significant health risks, including nephrological and hepatological issues. Addressing cadmium contamination is crucial for environmental and public health protection.

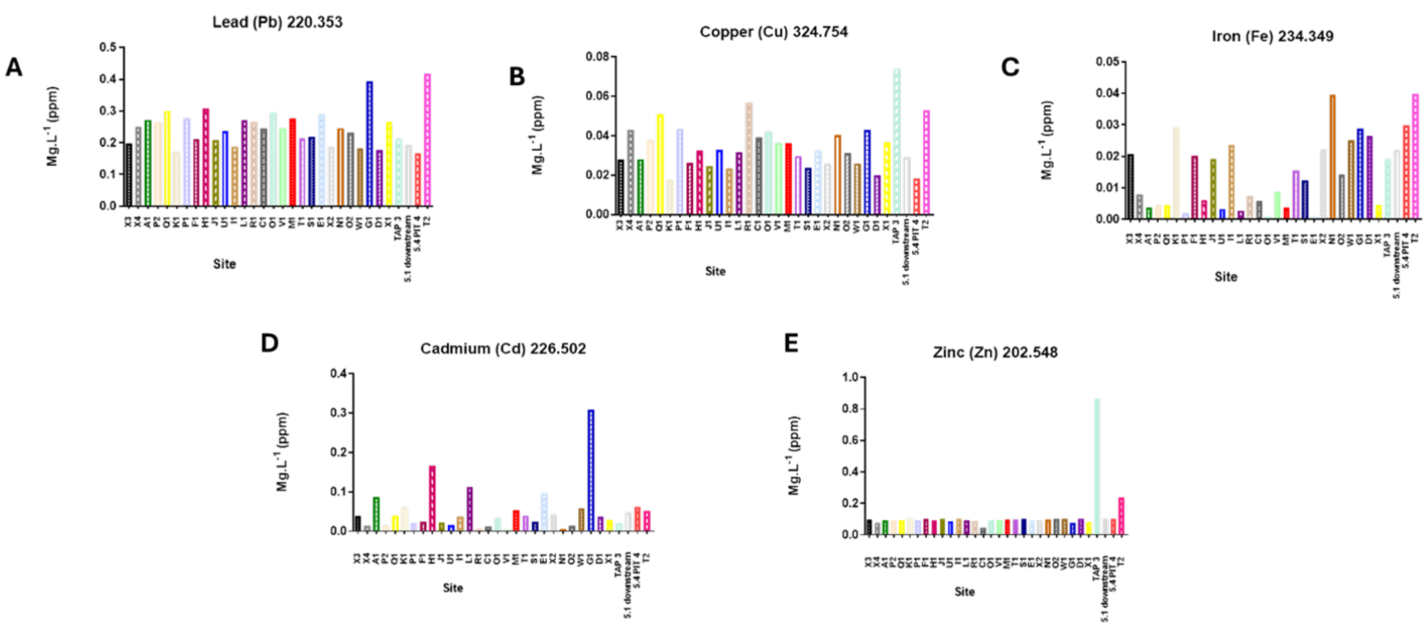

Figure 4.13. Heavy metals detected across the informal settlements

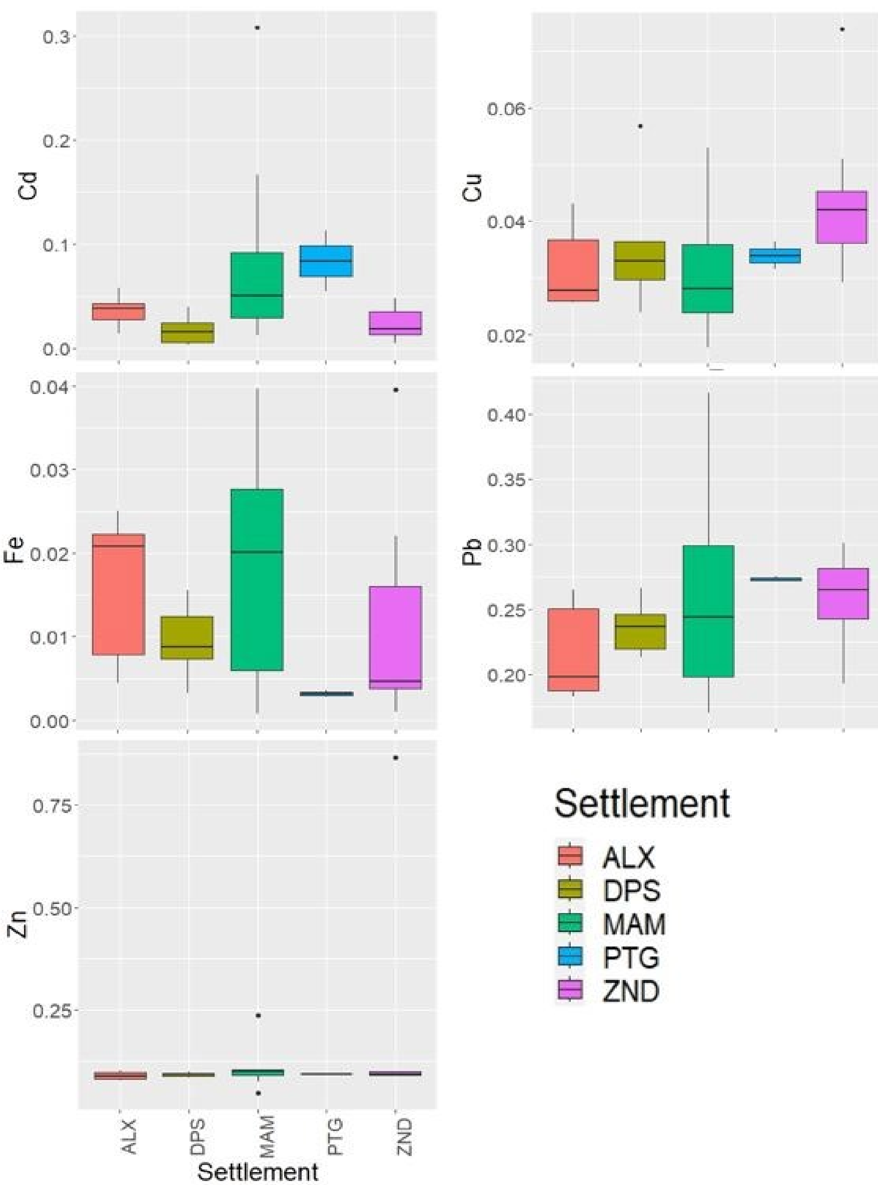

Figure 4.14. Boxplot illustrating the concentration of heavy metals (mg/L) detected at various sites of small water bodies. ALX, Alexandra; DPS, Diepsloot; MAM, Mamelodi; PTG, Pretoria gardens; ZND, Zandspruit

The presence of Zn was recorded at all sampled sites, with a slightly higher concentration observed at Diepsloot (T1). The ubiquitous detection of Zn across the surveyed sites highlights the widespread occurrence of this element within environmental water bodies (Figure 4.14). It is crucial to note that while Zn is an essential nutrient for the human body, excessive Zn intake, whether through water or other sources, can lead to zinc toxicity. Zinc toxicity can result in various health issues, including gastrointestinal distress, nausea, and vomiting, and interfere with the absorption of other essential minerals like Cu and Fe. This underscores the importance of monitoring and regulating Zn levels in water sources, especially in situations where elevated concentrations are identified, to safeguard public health and the quality of drinking water.

4.2.3 Physico-chemical parameters

4.2.3.1 pH levels

Figure 4.15 displays the physicochemical parameters measured at the Gauteng sites. The highest pH values were recorded in Mamelodi (G1 and H1) at an average of a pH 7.9, indicating more alkaline conditions. Most sites showed neutral pH levels, suggesting a generally stable environment. The SAWQG stipulate that the pH range for irrigation should be between 6.5 and 8.4, and for recreational usage, it should be between 6.5 and 8.5 (DWAF, 1996). The mean pH across all locations was within these intervals. The pH quantifies the concentration of hydrogen ions, reflecting the relative acidity or alkalinity of water. The optimal pH range for potable water is 6.5–8.5, as stipulated in WHO regulations. Elevated pH levels indicate a significant concentration of chloride, bicarbonate, or carbonate, among others (Uddin et al., 2014). The acceptable pH range for home water consumption in South Africa is 6–9, and the average across all locations was within this range (DWAF, 1996).

4.2.3.2 Electrical conductivity, turbidity, and total dissolved solids

Electrical conductivity denotes the extent to which a solution, such as stream water, can transmit an electric current. It denotes the concentration of dissolved ions, i.e. charged particles in the water. An elevation in EC may indicate the introduction of pollutants into the water. In an optimal environment, freshwater streams maintain an EC ranging from 150 to 500 µS/cm to sustain a variety of aquatic organisms (Mathur, 2015). Figure 4.15 provides insights into EC levels, with the highest values in Mamelodi (C1, G1) and Zandspruit (N1, R1, and Q1). Zandspruit demonstrated significantly higher levels when compared to Alexander and Mamelodi ($p < 0.001$). Although the levels were low, Diepsloot also demonstrated significantly higher levels when compared to Alexandra ($p < 0.001$). Despite this, the EC levels at all sites remain within the levels stipulated by the guidelines. Kumar (2012) has noted that water sources within this range are appropriate for home usage and irrigation purposes (Islam and Islam 2020).

The highest turbidity levels were recorded at Zandspruit N1 (170 NTU), Diepsloot U1 (130 NTU), and R1 (110 NTU), significantly exceeding the acceptable limits for both recreational and domestic water use. Diepsloot demonstrated significantly higher levels of turbidity than Mamelodi ($p < 0.055$). The fact that turbidity levels at all sites exceeded the recommended limits of 3 NTU for recreational use and 0–1 NTU for domestic use indicates a widespread issue with water clarity and quality across the sampled locations. This elevated turbidity can suggest the presence of pollutants, which may impair the suitability of the water for both human use and aquatic life, highlighting potential public health risks.

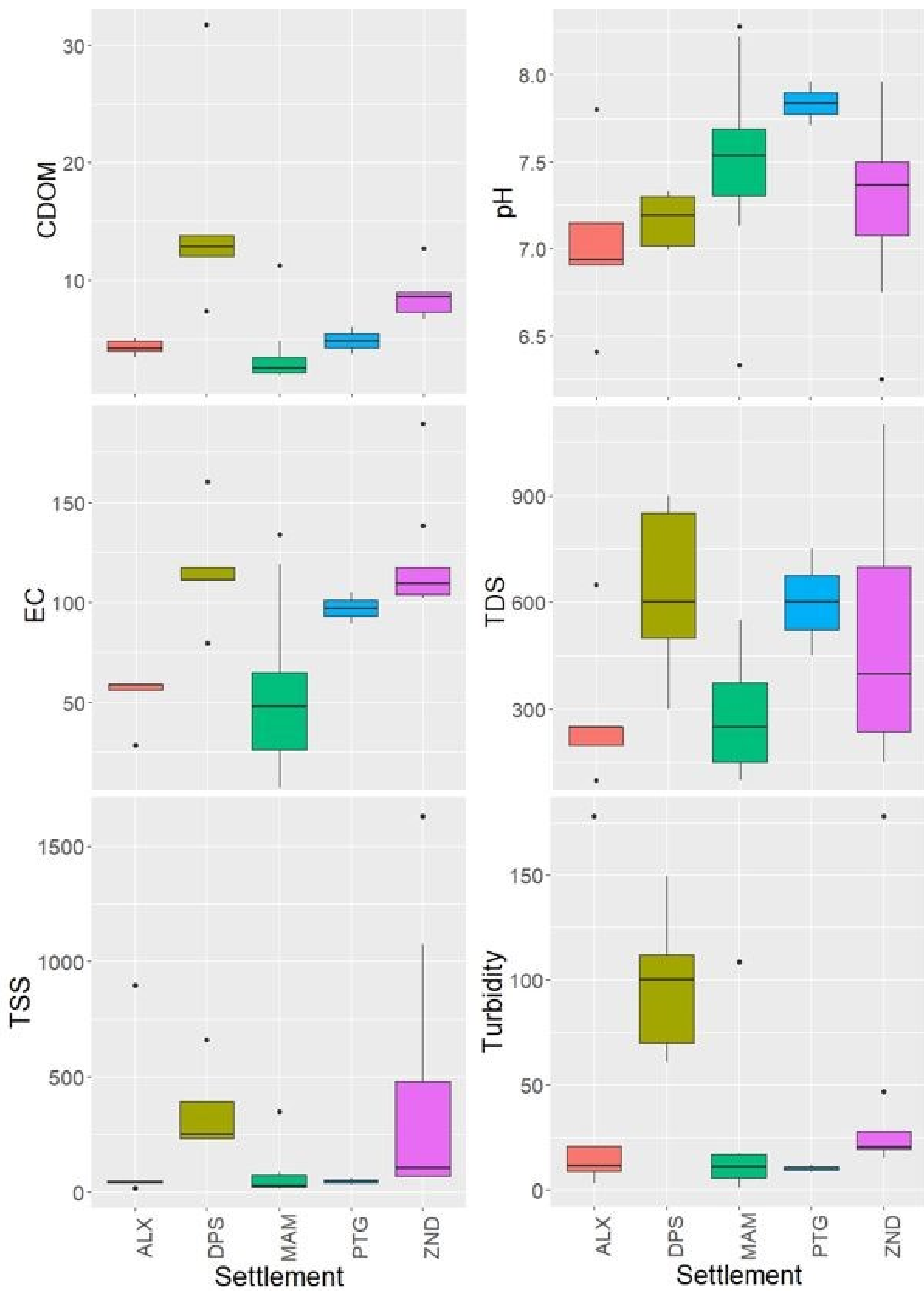

Figure 4.15. Water quality parameters measured in small water bodies in informal settlements in Gauteng. ALX, Alexandra; CDOM, coloured dissolved organic matter; DPS, Diepsloot; EC, electrical conductivity; MAM, Mamelodi; PTG, Pretoria Gardens; TDS, total dissolved solids; TSS, total suspended solids; ZND, Zandspruit

The TDS concentrations did not differ significantly between sites, but were highest in Pretoria Gardens (L1), Zandspruit (N1, P1, Q1), Diepsloot (R1, T1, V1) and Alexandra (X4). Elevated TDS could result from natural and anthropogenic sources, influencing water quality.

4.2.3.3 Total suspended solids and coloured dissolved organic matter

The SAWQG stipulate that TSS levels in aquatic habitats should not surpass 100 µg/L. Total suspended solid levels in Mamelodi (C1, D1), Zandspruit (N1, P2, P3), Diepsloot (R1, S1, T1, U1, V1) and Alexandra (W1) surpassed the threshold average. The remaining locations had TSS levels within the threshold; however, there was significant variability in the levels observed. This may be ascribed to informal housing being constructed near tiny water bodies and run-off that transports materials from the construction into the river. The suspended material comprises silt, clay, fine organic and inorganic particles, soluble organic compounds, plankton, and other tiny creatures. The presence of suspended particles often correlates with diminished water clarity, such as reduced light penetration or visibility (Department of Environmental Affairs, 2018). The presence of TSS in rain run-off has been identified as a primary contributor to contaminated sediments originating from metropolitan areas (Wakida et al., 2014). Torres and Bertrand-Krajewski (2008) concur that several contaminants in urban stormwater flows are associated with suspended particles.

The CDOM levels were the highest in Mamelodi (C1), Diepsloot (R1, S1, T1, and V1), and Alexandra (W1). Diepsloot exhibited significantly higher levels of CDOM than Pretoria Gardens, Mamelodi, Alexandra, and Zandspruit ($p < 0.001$). High CDOM levels indicate the presence of organic material, which affects water colour and quality (Figure 4.15).

Table 4.5. The ANOVA and Tukey honest significant difference test

Zandspruit and Mamelodi	EC	0.001	0.001	Physico-chemical
Diepsloot and Mamelodi	Turbidity	0.055	0.033	Physico-chemical
Diepsloot and Mamelodi	CDOM	0.001	0.001	Physico-chemical
Diepsloot and Alexandra	CDOM	0.001	0.002	Physico-chemical
Diepsloot and Pretoria Gardens	CDOM	0.001	0.037	Physico-chemical
Diepsloot and Zandspruit	CDOM	0.001	0.049	Physico-chemical
Diepsloot and Pretoria Gardens	*E. coli*	0.001	0.001	Microbial
Diepsloot and Mamelodi	*E. coli*	0.001	0.000	Microbial
Diepsloot and Alexandra	*E. coli*	0.001	0.001	Microbial
Diepsloot and Zandspruit	*E. coli*	0.001	0.001	Microbial
Zandspruit and Mamelodi	Chl-*a*	0.039	0.025	Microbial

CDOM, coloured dissolved organic matter; chl-*a*, chlorophyll-*a*; EC, electrical conductivity

The analysis of microbial contamination alongside physicochemical water quality indicators in Diepsloot and other informal settlements underscores significant ecological and public health risks. The elevated levels of *E. coli* and total Coliforms, coupled with high EC, turbidity, and TSS, indicate severe water pollution in these communities. These findings align with studies by Gqomfa et al. (2022) and Morole et al. (2022), who illustrated the detrimental effects of informal settlements on water quality in South Africa. Geographically, informal settlements such as Diepsloot, Alexandra, and Mamelodi are situated near polluted water sources, such as rivers or streams, which are subjected to contamination from unregulated waste disposal, industrial effluents, and stormwater run-off. This situation is typical across informal settlements in developing countries, where a lack of infrastructure and improper waste management exacerbate contamination.

In Diepsloot, the consistently high conductivity levels (exceeding 200 μS/cm in some sites) point to a high concentration of dissolved ions, likely from untreated sewage and industrial discharge. Similar conductivity levels have been observed in informal settlements like Kibera in Nairobi (Musa et al., 2021), where poor drainage systems and open sewers contribute to water pollution. The deteriorating infrastructure in Diepsloot reflects the broader trend in informal settlements across the globe, where rapid urbanisation and population growth have outpaced the development of adequate sanitation systems, leading to widespread pollution.

The high turbidity and TSS levels recorded in Diepsloot, particularly at sites R1, S1, and T1, signal severe water degradation. Turbidity and suspended solids not only diminish the aesthetic quality of water but also provide surfaces for microbial attachment, allowing pathogens such as *E. coli* to survive longer. This is consistent with similar findings in other informal settlements, such as in Jakarta, Indonesia (Sari et al., 2018), where poor sanitation and heavy sedimentation in water sources led to heightened risks of microbial contamination. In Diepsloot, high turbidity further hampers natural disinfection, as UV rays cannot penetrate the water to reduce microbial load.

The microbial analysis revealed alarmingly high *E. coli* concentrations (up to 1800 CFU/100 mL), significantly exceeding South Africa’s recommended water quality standards and pointing to severe faecal contamination. Such levels of contamination highlight the lack of basic sanitation infrastructure, as raw sewage is often discharged directly into water bodies. This issue is mirrored in other informal settlements, like those in Lagos, Nigeria (Adetola et al., 2020), where waterborne diseases proliferate due to poor waste and excreta management. The presence of high *E. coli* levels in these settlements is a clear indicator of the broader sanitation crisis that affects many informal communities globally.

In addition to microbial contamination, elevated levels of heavy metals such as Pb, Cu, and Zn were found in the water in Diepsloot, further compounding public health risks. Lead, potentially from industrial run-off and dilapidated infrastructure, presents significant neurodevelopmental risks, particularly for children. Zinc, although essential in trace amounts, was detected at relatively higher levels, which could exacerbate health problems in the community. Similar heavy metal contamination has been reported in water sources in informal settlements in Johannesburg (Dabrowski and De Klerk, 2013) and Rio de Janeiro (Silva et al., 2021), where industrial waste and inadequate sanitation infrastructure contribute to high levels of contamination.

4.3 WATER QUALITY INDEX

The study considered the WAWQI for irrigation and recreational water usage because the sampling points selected were on the edge of settlements. A total of 12 indicators (i.e., pH, EC, TDS, TSS, *E.coli*, total coliforms, Cd, Cu, Fe, Pb, Zn, and turbidity) were used in the calculation of the WAWQI. The WAWQI varied between 0.02 (C1) and 13.11 (G1) in the northern and southern parts of Gauteng, respectively. The WAWQI values indicate that the water in these rivers is fit for irrigation and industrial use, as shown by the WQI range formulated by Brown et al. (1972), Chatterji and Raziuddin (2002), and Yogendra and Puttaiah (2008). Taking into account the individual measured parameters, the study found that *E. coli* and turbidity levels were above the recommended SAWQG for recreational use. Meanwhile, TDS was found to be elevated above the recommended standard for agricultural water use. The deviation of the WAWQI from the SAWQG standards may result from the fact that the index has been mainly applied for domestic water consumption studies. Further to this, the WAWQI provides a single number that expresses the overall water quality of an area.

4.4 REMOTE SENSING TECHNIQUES FOR WATER QUALITY MAPPING: COASTAL

Five heavy metals (Cd, Cu, Pb, Fe and Zn) were analysed from the samples collected in September 2024, as in the inland analysis (Table 4.6). These heavy metals were analysed from 20 samples (n = 20).

Table 4.6. Summary of heavy metal concentrations (µg/L) collected in uMlazi informal settlement

	Cd	Cu	Fe	Pb	Zn
Min	0.086	0.176	–0.113	–0.063	–0.083
Max	0.315	0.233	1.170	0.053	–0.032
mean	0.166	0.186	0.016	–0.002	–0.066
std. dev	0.047	0.014	0.277	0.037	0.014
N	20	20	20	20	20

4.4.1 Correlation analysis

The PS dataset with eight multispectral bands was used for the study. This version of PS data has additional bands in the coastal, green, yellow and red edge. Figure 4.16 shows the correlation between the heavy metals and the 8-band PS data.

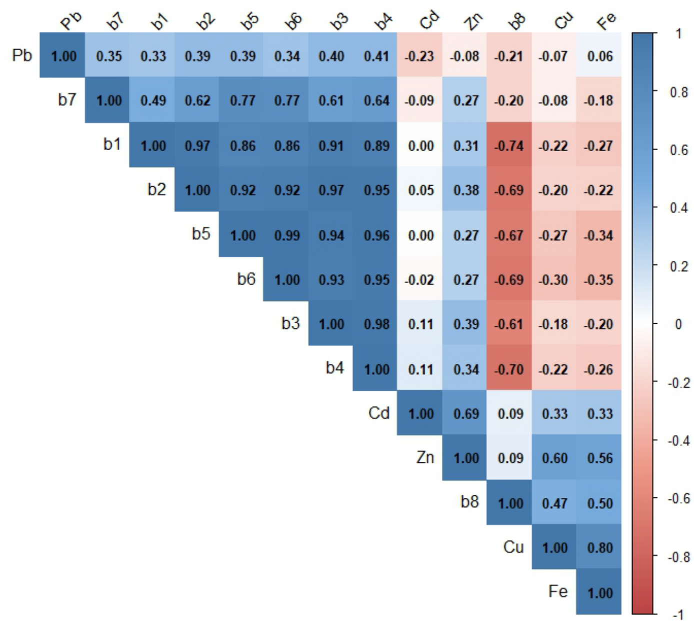

Figure 4.16. Correlation analysis between heavy metals and PS data acquired for uMlazi informal settlement along the KwaZulu-Natal coast. b1, ; b2, ; b3, ; b4, ; b5, ; b6, ; b7, ; b8,

Generally, the remote sensing spectral bands and the heavy metals were weakly correlated. However, Pb and the green band were correlated at r = 0.41, while no correlation (r = 0.00) was found between Cd and both green and yellow bands. The strongest correlation between Pb and the green band suggests that, on its own or within a computed index, the green band can improve on the estimation of heavy metals, especially Pb.

4.4.2 Water quality mapping

A total of five models resulted from the incorporation of remote sensing variables for mapping water quality in uMlazi small water bodies. Generally, the models used were not significant, except for the one predicting Zn concentration ($p = 0.01$; RMSE = 0.014). This model is nullified since, in reality, it detects no levels of Zn because the sample concentrations failed to reach detectable levels. Table 4.7 summarises the models used. Detailed descriptions of the resultant models are shown in Appendix B. Figure 4.17 indicates the measured and predicted concentrations of the heavy metals. It is worth noting that in the current datasets, the samples with negative values (i.e. below the detectable limits) were retained throughout the modelling processes. From the PS data, the NDWI was significant in several models, including for Cd and Zn ($p < 0.05$), suggesting the contribution of green and infrared bands for the estimation of heavy metals. The red and NIR spectral bands were useful to detect Fe in the water – findings that were made elsewhere by Lin et al. (2024).

Table 4.7. Summary of the final model calibrated and used for prediction, and the respective validation measures from test data

Indicator	R^2	P-value	RMSE	MAD
Cd	0.31	0.10	0.050	0.026
Cu	0.30	0.10	0.015	0.008
Fe	0.35	0.07	0.280	0.132
Pb	0.59	0.24	0.030	0.020
Zn	0.59	0.01	0.014	0.009

MAD, mean absolute deviation; RMSE, root mean square error

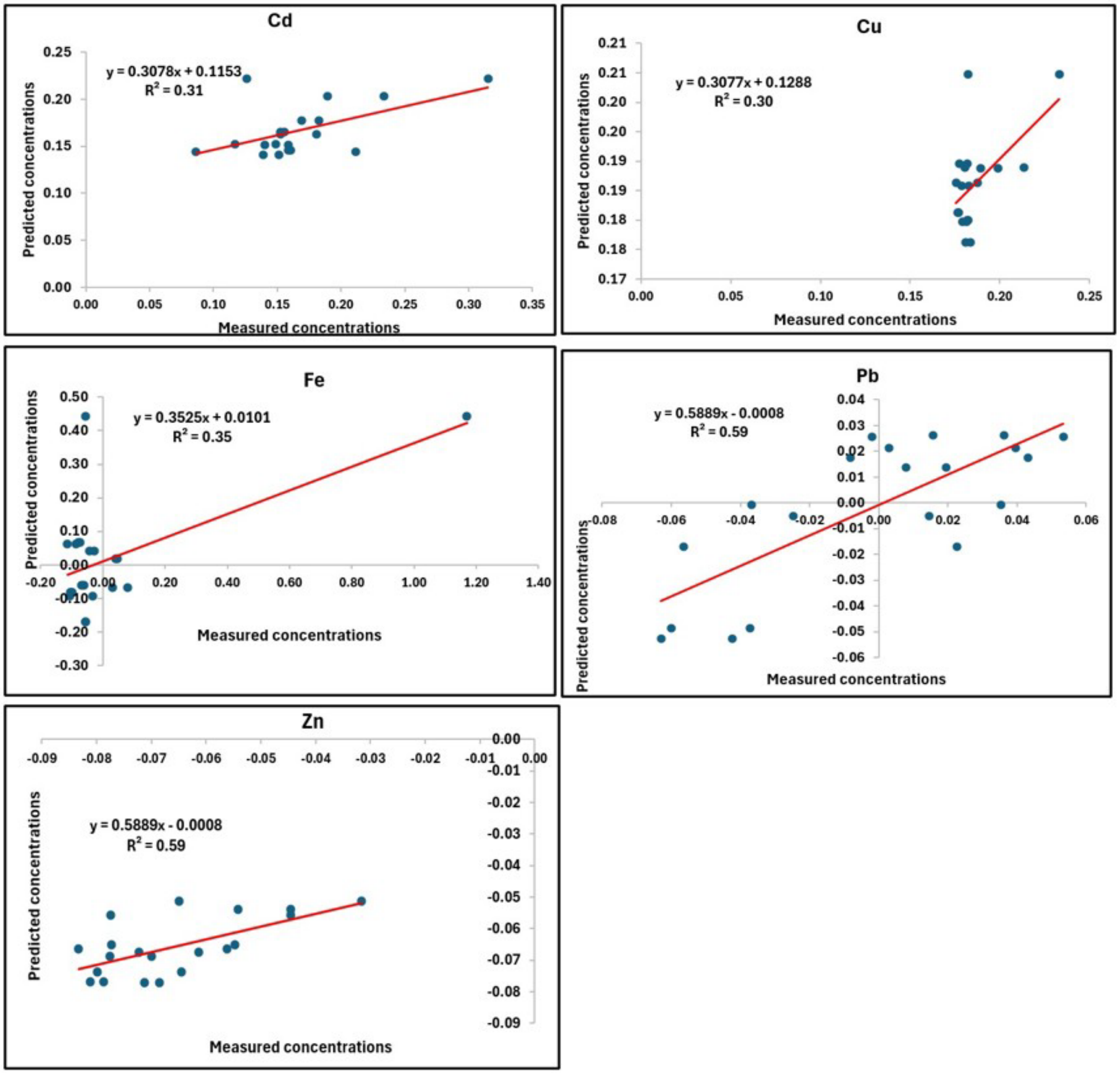

Figure 4.17. Measured and predicted concentrations of heavy metals

The heavy metal analysis of water samples collected from uMlazi informal settlement revealed concerning concentrations of specific metals, some exceeding the South African Water Quality Standards. A summary of the heavy metal WQI for irrigation water is shown in Figure 4.15. Elevated Pb levels were detected at varying concentrations in the sampled sites, likely attributed to run-off from ageing infrastructure and contamination from surrounding activities. Lead concentrations at these sites did not surpass the permissible limit of 0.01 mg/L. Copper levels were notably high at sites P4 and P10, potentially resulting from sewage accumulation. Although copper is an essential nutrient, excessive exposure can cause gastrointestinal and hepatic damage.

Iron concentrations were elevated at site P10, exceeding the acceptable limit of 0.3 mg/L, which may lead to gastrointestinal distress and liver complications. The high levels detected in these sites suggest natural sources, exacerbated by poor drainage systems, which were evident as shown in the photos in Appendix A. The site was also near a construction site that could serve as a source of contamination. Additionally, Cd, a toxic metal linked to industrial pollution and battery waste, was present at sites P3, P6, and P10, exceeding the threshold of 0.003 mg/L. Chronic exposure to Cd is associated with nephrological and hepatological disorders, underscoring the urgent need for mitigation strategies. Furthermore, Zn, while essential in trace amounts, was detected at all sites, albeit at low levels, not surpassing the recommended limit of 5 mg/L.

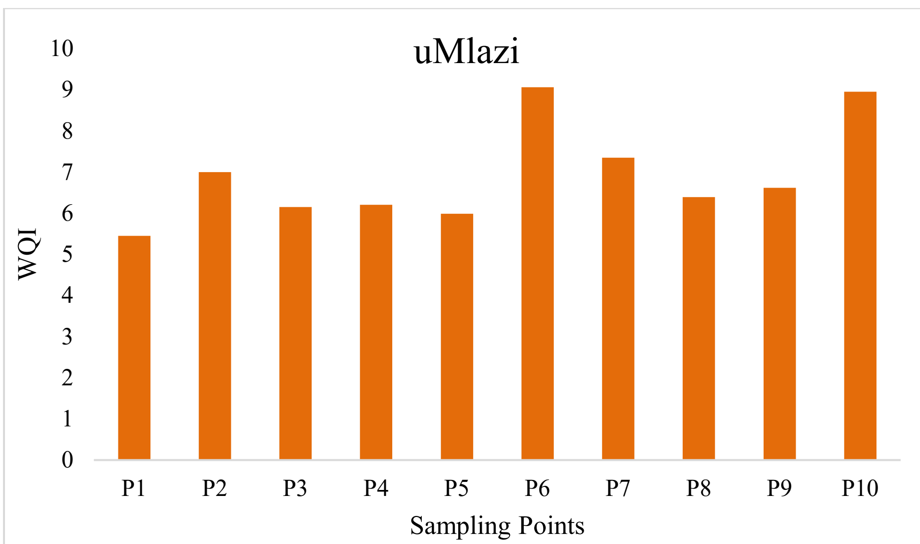

Figure 4.18. Mean Water Quality Index (WQI; n = 10) of sampling sites in uMlazi

All sampled sites in uMlazi exhibited extensive domestic contamination of small water bodies, as evident in the images, with residents living in extremely poor conditions. Children are particularly vulnerable, being exposed to open sewage, which poses severe health risks. In one location, the area was heavily impacted by air pollution from the open sewage system, with residents reporting various health ailments linked to prolonged exposure. Beyond the immediate health concerns, the deteriorating environmental conditions have profound social implications, as residents struggle to maintain a decent quality of life in such an environment. The combination of heavy metal contamination, poor sanitation, and air pollution negatively affects both physical and mental well-being, underscoring the urgent need for comprehensive interventions. Immediate action is required, including stringent water quality monitoring, the development of proper sanitation infrastructure, and targeted public health initiatives to safeguard the well-being of this vulnerable community.

INLAND AND COASTAL WATER QUALITY: COMPARISON

Table 4.8. One-way analysis of variance for heavy metals detected in water bodies at inland and coastal informal settlements

Heavy metal	df	F value	p-value
Cadmium (Cd)	5	13.92	0.00314
Copper (Cu)	5	349.4	0.002
Lead (Pb)	5	62.27	0.002
Iron (Fe)	5	0.004	1.000
Zinc (Zn)	5	7.9	0.00208

The concentrations of all heavy metals across both inland and coastal informal settlements differed significantly ($p < 0.05$) except for Fe (Table). However, the significant difference in concentrations was observed mainly from samples collected in uMlazi compared to other inland settlements in Gauteng province. The largest variation was observed between Zandspruit and uMlazi, where Cd, Cu, Pb, and Zn were found to be significantly different between these inland and coastal informal settlements.

Table 4.9. The Tukey HSD results amongst the inland and coastal informal settlements.

Heavy metal	Settlements	p-value
Cd	UML-ALX	0.0001
	UML-DPS	0.00001
	ZND-UML	0.000001
Cu	UML-ALX	0.000001
	UML-DPS	0.000001
	UML-MLD	0.000001
	UML-PTG	0.000001
	ZND-UML	0.000001
Pb	UML-ALX	0.000001
	UML-DPS	0.000001
	UML-MLD	0.000001
	UML-PTG	0.000001
	ZND-UML	0.000001
Fe	-	-

Zn	UML-MLD	0.002
	ZND-UML	0.0001

Table 4.10. The final coastal water quality predictive model

Variable	Co-efficient	p-value
Intercept	-1.185	0.02 *
Blue-green index	2.284	0.04 *
Blue-red index	-1.641	0.06
Green-red index	-0.532	0.19
Red-near infrared index	0.500	0.06

CHAPTER 5: CONCLUSIONS & RECOMMENDATIONS

This section presents the conclusions drawn and recommendations made in relation to this project and future projects.

5.1 CONCLUSIONS

The following conclusions were drawn from the project:

- There is notably high coexistence between *E. coli* and total coliform concentrations in small water bodies of the selected informal settlements. This suggests that the small- to micro- water bodies in the selected informal settlements are prone to faecal pollution, which could endanger the health of the proximal population. The high level of these contaminants is attributed to the fact that most of the small water bodies in the informal settlements tend to comprise effluent from leaking sewerage systems.
- Diepsloot, Mamelodi and Zandspruit informal settlements tend to have considerable quantities of both microbial and physicochemical contaminants in their small surface water bodies. This finding is important when considering the likelihood of the communities in these settlements suffering from waterborne and water-related illnesses and to prioritise intervention strategies when needed.
- There were relatively low correlations between the remotely sensed data and the spectral bands of the PS satellite, with a relatively strong correlation existing between turbidity and the blue band. The weakest correlations existed between *Salmonella* presence/absence and the blue and red bands. Additionally, the heavy metals were weakly correlated with the PS data in this study. However, it was found in this study that the computation of predictive models using the PS-derived indices improved the modelling capability compared to when using a single-band approach.
- The small- to micro- water body thematic layer was successfully extracted from the PS data through an MLC with an overall accuracy of 0.9 and a kappa coefficient of 0.85. The sizes of extracted water bodies ranged from 9 m^2 to 29 078 m^2. The extraction of small water bodies allows for purposive analysis of water quality and the delineation of surface water bodies that may need urgent management attention, thus reducing the cost associated with haphazard remediation of water quality in the informal settlements.
- The WAWQI calculated from the collected data suggests that the water bodies around some of the informal settlements could be used for irrigation purposes (WAWQI < 50), according to the SAWQG. However, caution should be exercised, especially due to the recent outbreak of cholera in Gauteng.
- The coastal PS data exhibited weaker correlations with the heavy metals, although the green, red and near-infrared spectral bands showed a potential for surface water quality mapping of heavy metals. This finding should be further investigated, as corroborative studies will further enhance the utility of these common multispectral bands.

- The WAWQI values in the coastal areas (except one) were < 10. However, overall, the inland water bodies had much lower WAWQI values than those obtained at the coastal informal settlement of uMlazi. Whether values above or below 10 mean deteriorated or acceptable water quality, respectively, remains a subject that needs further testing and calibration of the index.

5.2 RECOMMENDATIONS

The following recommendations stem from this project's findings:

- Water quality data should be collected at least seasonally in informal settlements to ascertain the seasonal fluctuations of water quality parameters in these areas.
- Water quality parameters not included in this project should form part of future data collection and analysis exercises.
- The results of the WAWQI model calibration should be tested on data collected in other seasons and in different informal settlements than the inland ones, preferably the coastal informal settlements' surface water bodies.
- Human risk research should be conducted on the vulnerability of communities to potential waterborne and water-related diseases, especially during periods of floods.
- There should be public awareness campaigns by authoritative bodies within the municipality on the status of water quality within their respective informal settlements.
- The use of data with a high spectral resolution, e.g. 8-band PlanetScope data, is recommended for future research.
- The mapping of potential and actual small water bodies in informal settlements should be considered for improving the understanding of the potential risk of contaminated water bodies to nearby informal settlement communities, especially during periods of floods.

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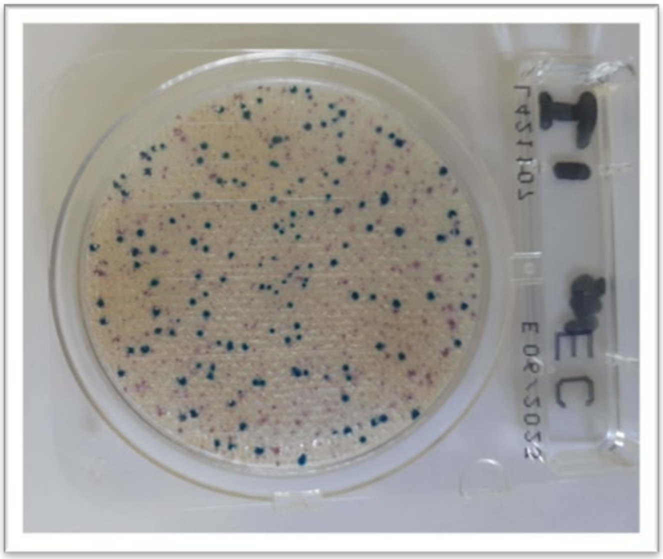
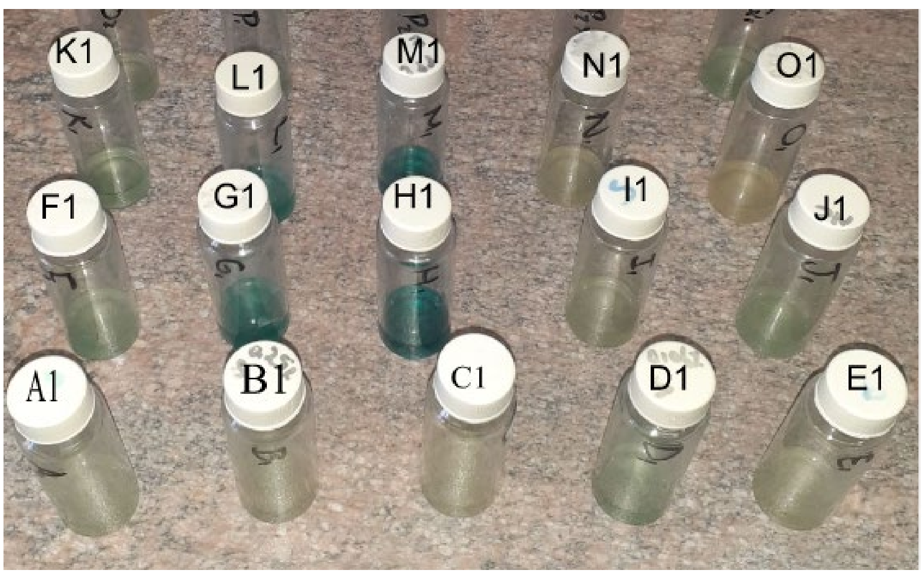
APPENDIX A: SUPPLEMENTARY INFORMATION



Sample I1 was subjected to plating on Brilliance™ *E. coli*/coliform Selective Agar following the designated incubation period



Some of the *Salmonella* samples prepared for laboratory analysis

Some of the small water bodies sampled within the informal settlements in Gauteng in 2022.

APPENDIX B: MODELS

```
Call:
lm(formula = Cd ~ b2 + b8 + ndwi, data = a)

Residuals:
      Min        1Q    Median        3Q       Max 
-0.095856 -0.011537 -0.002602  0.013465  0.093344 

Coefficients:
              Estimate Std. Error t value Pr(>|t|)  
(Intercept)  5.180e-01  1.883e-01   2.751   0.0142 *
b2          -4.655e-04  2.549e-04  -1.826   0.0865 .
b8           9.802e-05  3.823e-05   2.564   0.0208 *
ndwi        -6.796e-01  2.679e-01  -2.537   0.0220 *
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.04303 on 16 degrees of freedom
Multiple R-squared:  0.3078,	Adjusted R-squared:  0.178 
F-statistic: 2.371 on 3 and 16 DF,  p-value: 0.1088
-----------------------------------------------------------------

Call:
lm(formula = Cu ~ b4 + b6 + ndwi, data = a)

Residuals:
       Min         1Q     Median         3Q        Max 
-0.0227170 -0.0072581 -0.0000603  0.0027881  0.0281830 

Coefficients:
              Estimate Std. Error t value Pr(>|t|)  
(Intercept)  2.875e-02  7.747e-02   0.371   0.7154  
b4           2.776e-04  1.295e-04   2.143   0.0478 *
b6          -9.734e-05  5.288e-05  -1.841   0.0843 .
ndwi         1.078e-01  5.274e-02   2.045   0.0577 .
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.01274 on 16 degrees of freedom
Multiple R-squared:  0.308,	Adjusted R-squared:  0.1782 
F-statistic: 2.373 on 3 and 16 DF,  p-value: 0.1086
-----------------------------------------------------------------

Call:
lm(formula = Zn ~ b8 + ndwi, data = a)
```

```
Residuals:
       Min         1Q     Median         3Q        Max 
-0.0216231 -0.0067731 -0.0005893  0.0093022  0.0196675 

Coefficients:
              Estimate Std. Error t value Pr(>|t|)    
(Intercept) -5.676e-02  9.954e-03  -5.702 2.59e-05 ***
b8           2.792e-05  8.685e-06   3.215  0.00508 ** 
ndwi        -1.234e-01  3.667e-02  -3.365  0.00367 ** 
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.0116 on 17 degrees of freedom
Multiple R-squared:  0.4052,	Adjusted R-squared:  0.3353 
F-statistic: 5.791 on 2 and 17 DF,  p-value: 0.01208
------------------------------------------------------------------
Call:
lm(formula = Fe ~ b2 + b7 + b8, data = a)

Residuals:
     Min       1Q   Median       3Q      Max 
-0.49991 -0.09776 -0.01048  0.06987  0.72609 

Coefficients:
              Estimate Std. Error t value Pr(>|t|)  
(Intercept) -0.5483591  0.5436764  -1.009   0.3282  
b2           0.0015014  0.0009842   1.526   0.1466  
b7          -0.0008954  0.0006802  -1.316   0.2066  
b8           0.0003436  0.0001258   2.730   0.0148 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.2431 on 16 degrees of freedom
Multiple R-squared:  0.3525,	Adjusted R-squared:  0.2311 
F-statistic: 2.904 on 3 and 16 DF,  p-value: 0.06699
-----------------------------------------------------------------

Call:
lm(formula = Pb ~ b1 + b2 + b3 + b4 + b5 + b6 + b7 + b8 + ndwi, 
    data = a)

Residuals:
     Min       1Q   Median       3Q      Max 
-0.03950 -0.01862  0.00000  0.01862  0.03950 

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
```

```
(Intercept)  2.5352855  1.2586540   2.014   0.0717 .
b1          -0.0045456  0.0022315  -2.037   0.0690 .
b2           0.0097178  0.0048526   2.003   0.0731 .
b3          -0.0098185  0.0052998  -1.853   0.0936 .
b4          -0.0022714  0.0014251  -1.594   0.1420
b5           0.0100737  0.0047029   2.142   0.0578 .
b6          -0.0026035  0.0010100  -2.578   0.0275 *
b7          -0.0038574  0.0020989  -1.838   0.0959 .
b8           0.0004607  0.0002309   1.995   0.0740 .
ndwi        -0.6358184  0.5638835  -1.128   0.2858
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.03279 on 10 degrees of freedom
Multiple R-squared:  0.5889,    Adjusted R-squared:  0.2188
F-statistic: 1.591 on 9 and 10 DF,  p-value: 0.2395
```