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JÚLIO CARDOSO PEREIRA

SMART WATERSHED MONITORING: A MULTI-SOURCE DATA ARCHITECTURE FOR REAL-TIME AND HISTORICAL ANALYSIS FOR DECISION SUPPORT

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Dissertação apresentada ao Programa de Pós-Graduação *Strictu Sensu* em Sustentabilidade (PPGS) do Centro de Economia e Administração (CEA) da Pontifícia Universidade Católica de Campinas (PUC-Campinas) como requisito parcial para a obtenção do título de Mestre em Sustentabilidade.

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JULIO CARDOSO PEREIRA

SMART WATERSHED MONITORING: A MULTI-SOURCE DATA ARCHITECTURE FOR REAL-TIME AND HISTORICAL RIVER BASIN ANALYSIS FOR DECISION SUPPORT.

Este exemplar corresponde à redação final da Dissertação de Mestrado em Sustentabilidade da PUC-Campinas, e aprovada pela Banca Examinadora.

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ABSTRACT

This study presents a theoretical proposal for an integrated water monitoring system for the PCJ region, based on a comprehensive literature review and feasibility analysis. No field implementation or experimental validation was carried oct. It addresses the challenges of water scarcity, pollution, and flood risks due to urbanization and climate change. The study evaluates the integration of *in-situ* sensors, satellite remote sensing, and Unmanned Aerial Vehicles with advanced data analytics, Internet of Things, and Artificial Intelligence. A high-level Decision Support System architecture is proposed, combining real-time and historical data for water quality indicators, flood forecasting, and pollution detection. The methodology involves analyzing existing technologies, communication infrastructures, and feasible sensor deployment. Results show that combining remote sensing with IoT-based networks enhances monitoring capacity, providing actionable insights for stakeholders. Furthermore, the study highlights recent advances in microplastic detection using AI, optical sensors, and microfluidic technologies. The proposed system aims to support the PCJ Agency, civil defense, and local governments in proactive water resource management through predictive analytics and real-time dashboards, however its modular architecture make it feasible to be implemented by other agencies controlling watersheds. This work is inherently interdisciplinary research because it integrates concepts, methods, and technologies from multiple scientific and engineering fields to solve a complex socio-environmental problem.

Keywords: Water Management, Water Quality Index, Remote Sensing, Microplastic Detection, Flood Forecasting, Environmental Data Integration

RESUMO

Este estudo apresenta uma proposta teórica para um sistema integrado de monitoramento da água na região PCJ, com base em uma revisão bibliográfica abrangente e em uma análise de viabilidade. Não foram realizadas implementação em campo nem validação experimental. Aborda os desafios da escassez hídrica, poluição e riscos de inundações devido à urbanização e às mudanças climáticas. O estudo avalia a integração de sensores *in-situ*, sensoriamento remoto por satélite e Veículos Aéreos não Tripulados (*drones*) com análise avançada de dados, Internet das Coisas e Inteligência Artificial. Uma arquitetura de alto nível de um Sistema de Apoio à Decisão é proposta, combinando dados históricos e em tempo real para indicadores de qualidade da água, previsão de inundações e detecção de poluição. A metodologia envolve a análise de tecnologias existentes, infraestruturas de comunicação e implantação viável de sensores. Os resultados mostram que a combinação de sensoriamento remoto com redes baseadas em IoT aumenta a capacidade de monitoramento, fornecendo percepções com ação viável. Além disso, o estudo destaca os avanços recentes na detecção de microplásticos usando IA, sensores ópticos e tecnologias microfluídicas. O sistema proposto visa apoiar a Agência PCJ, defesa civil e governos locais na gestão proativa dos recursos hídricos por meio de análises preditivas e painéis em tempo real, entretanto a arquitetura modular proposta torna-a capaz de ser implementada por outras agências que controlam bacias hidrográficas. Este trabalho é inerentemente a pesquisa interdisciplinar pois integra conceitos, métodos e tecnologias de múltiplos campos científicos e de engenharia para resolver um problema socioambiental complexo.

Palavras-chave: Gestão da Água, Índice de Qualidade da Água, Sensoriamento Remoto, Detecção de Microplásticos, Previsão de Inundações, Integração de Dados Ambientais

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LIST OF ABBREVIATIONS AND ACRONYMS

AI	Artificial Intelligence
ANA	National Water and Sanitation Agency (Agência Nacional de Águas)
API	Application Programming Interface
BOD	Biochemical Oxygen Demand
CETESB	State of São Paulo Environmental Company (CETESB - Companhia Ambiental do Estado de São Paulo)
CI/CD	Continuous Integration/Continuous Deployment
COD	Chemical Oxygen Demand
DL	Deep Learning
DFT	Data Fusion Techniques
DO	Dissolved Oxygen
DR	Disaster Recovery
DSS	Decision Support System
EPA	Environmental Protection Agency (USA)
ETL/ELT	Extract Transform and Load/Extract Load and Transform (data)
FAPESP	São Paulo Research Foundation (Fundação de Amparo à Pesquisa do Estado de São Paulo)
FSO	Fish Swarm Optimization
GDP	Gross Development Product
GIS	Geographic Information Systems
GPS	Global Positioning System
GSM	Global System for Mobile Communication
GWO	Gray Wolf Optimization
IoT	Internet of Things
LSTM	Long Short Term Memory
M2M	Machine to Machine
ML	Machine Learning
MPC	Microplastic
OS	Operacional System
PCJ	Piracicaba, Capivari, and Jundiaí River Basins
RS	Remote Sensing
SMS	Short Message System
TDS	Total Dissolved Solids
TSS	Total Suspended Solids

UAV	Unmanned Aerial Vehicle
VPN	Virtual Private Networks
WDS	Water Distribution System
WHO	The World Health Organization
WMS	Water Monitoring System
WQI	Water Quality Indicator
WQX	Water Quality Index
WSN	Wireless Sensor Networks

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1 INTRODUCTION

Water availability has become a scarce resource around the world, especially due to rapid urbanization and industrialization which are straining river systems beyond their capacity to meet water demands, implying that rivers and stream systems may not meet the demand for water supply.

Complexities are increased due to climate changes and irregular rainy seasons implying the efficient and continuous monitoring of surface water dynamics has become essential (Bhat; Dar; Hamid, 2022; Yue et al., 2023). Such monitoring frameworks are indispensable not only for understanding current water availability but also for developing adaptive strategies that can enhance the resilience of aquatic ecosystems against anthropogenic pressures

According to Abimbola et al. (2024) pollution resulting from plastic has been identified as one of the most significant issues, projected to reach 1,200 million tons by 2060. The extensive use of plastic results from its resilience, resistance to degradation, ease of processing and lightweight, however plastic is not biodegradable.

Monitoring water quality and availability *in-situ* presents complexities, such as access to remote regions resulting in high costs and low frequency of sampling (Pérez-García et al., 2024), since contaminant detection must be performed right after the sample transportation in a laboratory by skilled personnel using specialized technology (Zulkifli; Rahim; Lau, 2018).

The integration of Unmanned Aerial Vehicles (UAVs) into water monitoring systems (WMS) has been extensively explored by evaluating challenges, opportunities associated for mapping and monitoring surface water resources; highlighting the potential to provide near real-time, high-resolution data, which is crucial for effective water resource management. Equipped with multispectral cameras UAVs can monitor water quality parameters such as turbidity and chlorophyll-a concentrations. They can also be used to collect water samples across various scenarios related to in water quality monitoring (De Keukelaere et al., 2023; Lariosa et al., 2024; Sibanda et al., 2021).

Remote sensing may constitute an important tool resulting from advancement in satellite and sensors technology, making it useful for, among others, oil pollution detection and flood assessment, however it requires coverage of the region under scrutiny and data availability (Nagaraj; Kumar, 2024). Therefore, optimizing data acquisition protocols remains vital for ensuring the reliability of satellite-based environmental monitoring.

Internet of Things (IoT) technology along with data analysis could provide important information regarding water quality and availability (Baspakova et al., 2021), which brings to one common problem, which is the absence of low-cost sensors that would cover several types of contaminants (Lambrou et al., 2014). Addressing these cost-related barriers is essential to enable the widespread deployment of smart water management systems.

Once the complexities of collecting and processing large volumes of data from diverse sources are resolved, a Decision Support System (DSS) can be implemented. It will enable data-driven decision-making by providing tools for simulation, modeling, and visualization (Delen, 2002; Power, 2002).

As an example, three water monitoring and management DSS are presented:

- Water Evaluation and Planning System. An integrated water resources planning by simulating water demand, supply, runoff, infiltration, and other processes (Water Evaluation and Adaptation Planning, 2025).
- Aquatool DSS Suite. Supports decision-making in river basin management under the European Union Water Framework Directive (Aquatool, 2025).
- eWater Source. A national hydrological modeling platform used by the Australian government agencies for water resource planning (E Water Group, 2025).

Combining water flow, volume, flood information, information from sensing sources, and Water Quality Indicators (WQIs) with historical data through statistical models and Artificial Intelligence (AI) will create new monitoring opportunities. Hence, this work addresses the following research question: how can we bring transparency and capacity to allow early detection of unusual events and enable preemptive actions?

As of today, there is gap related to the availability of a WMS in Brazil that would provide support for analyzing data acquired from various sources, offer analytical models, deliver user-friendly interfaces with dashboard, and allow for sandbox analysis[1].

[1] Practice of exploring, testing, or experimenting with data, algorithms, or models in a controlled and isolated environment, allowing for data scientists to evaluate ideas, assess risks, and test hypotheses without affecting production systems or core databases

This work is inherently interdisciplinary because it integrates concepts, methods, and technologies from multiple scientific and engineering fields into a unified framework to solve a complex socio-environmental problem. It combines hydrology and environmental science to understand water quality, microplastic pollution (MPC), flood dynamics; computer science and data engineering to design IoT architectures, cloud infrastructures, Artificial Intelligence/Machine Learning (AI/ML) models; and remote sensing and geospatial analysis to incorporate satellite UAV data into monitoring workflows. It also draws on materials science and analytical chemistry through the discussion of microfluidic, optical, and biosensing technologies for pollutant detection. Additionally, it incorporates public policy and water-governance perspectives by aligning technological proposals with the operational needs of Brazilian water-resource institutions.

1.1 Objectives

This work aims at investigating combinations of available technologies related to monitoring water bodies (such as locally placed sensors, satellite feed, and UAVs) as means to provide data that, when analyzed in conjunction of available historical information, will allow for a foundation of a modern DSS.

1.2 Specific Objectives

- Analyze the contribution of available technical literature on monitoring water systems.
- Seek possible combinations of monitoring techniques.
- Propose high level collecting architecture and presentation alternatives as to provide a foundation for a DSS.
- Assess the feasibility of applying advanced monitoring techniques in Piracicaba, Capivari, and Jundiaí River Basins (PCJ).

1.3 Research Problem

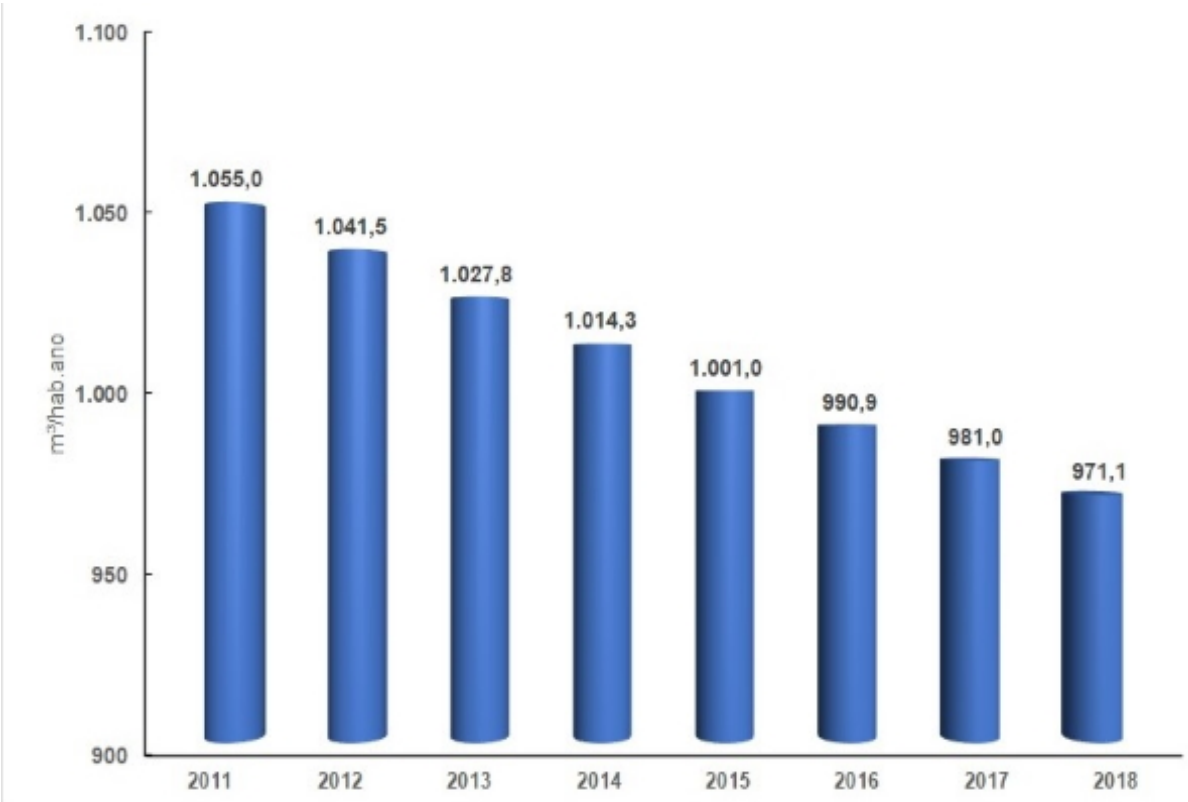
In Brazil, the National Water and Sanitation Agency (ANA) established the River Basin Committees, entities belonging to the National Water Resources Management System. These committees constitute a forum where representatives of the community of a river basin discuss

and deliberate on the management of water resources, sharing stewardship responsibilities with the public authorities (Ministry of National Integration and Regional Development, 2025).

PCJ Region covers 76 municipalities, 71 of which are in the States of São Paulo and 5 in Minas Gerais. With approximately 5.85 million inhabitants in 2019, the region stands out from an economic point of view representing 17% of the Gross Development Product (GDP) of the São Paulo State in 2014. It also concentrates one of the most important transport infrastructure networks in the country, also includes a dense road network and the Viracopos Airport, which is the largest in terms of cargo transport volume in the Country (PCJ River Basin Agency, 2025).

According to PCJ River Basin Agency, (2025), although the region has many water sources, PCJ Region have very limited water availability due to population growth, extensive utilization by industries, and pollution, indicating a trend of continuous reduction in the amount of water availability. For example, the water supply per inhabitant in this region is approximately 980 m³/inhabitant-year, which is considered unsatisfactory according to the reference values adopted in the State of São Paulo, which defines a situation with less than 1,500 m³/inhabitant-year as critical (see Figure 1).

Figure 1: Water availability/inhabitant



Source: PCJ River Basin Agency (2025)

The PCJ Agency is the executive arm of PCJ Committees, being responsible for developing water resource management instruments in the PCJ Region, and for managing financial resources. Such resources are comprised from fees related to water use in rivers under the jurisdiction of the Union and the state of São Paulo, as well as from the financial compensation/royalties from the hydroelectric sector. It is a legally established as a non-profit entity, with its own administrative and financial structure.

As of today, PCJ Agency collects and presents important information such as water flow, quality, capacity and availability of various reservoirs and rainfall indicators; however, it does not share water quality indicators and flood forecasting (PCJ Consortium, 2025). This lack of integrated data limits the capacity for early warning responses and proactive environmental management in the region.

As an example, in July 2024, Piracicaba River and its tributaries recorded two major fish deaths. The first was on the 7th, in the urban area of Piracicaba (São Paulo State, SP). The other case began on the 15th, in the Tanquã neighborhood, which is an environmental protection area. According to the Environmental Company of the State of São Paulo (CETESB), this occurred due to agro-industrial pollutants released irregularly by a sugar and alcohol plant in Rio das Pedras, São Paulo State (Giantomaso; Assencio; Del Santo, 2024).

Still another example in the same region, in January 2022 heavy rainfall caused the Piracicaba River to exceed its overflow threshold of 4.70 meters, leading to the inundation of homes and streets in various neighborhoods. During October 2023 severe storm resulted in the Piracicaba River reaching a depth of 4.43 meters, approaching its overflow point. This event led to road closures, property damage, and the displacement of several families (EPTV, 2023).

1.4 Justification

In 2023, ANA outlined priorities for 2025 and 2026, focusing on reducing water losses, improving service quality, and standardizing regulatory practices. These initiatives aim to address inefficiencies, as studies have shown that 37.8% of distributed water is lost before reaching consumers, underscoring the necessity for improved infrastructure and management practices (Monitor Mercantil, 2025).

With the evolution of telecommunications, particularly cellular networks, IoT, AI, and sensing (either locally deployed or from satellite), there is a large supply of available (near)

real-time data, which combined with statistical models and historical information, is capable of providing essential information that will better serve the PCJ Agency, general population, government, Civil Defense, and ultimately every stakeholder.

Therefore, the development of an integrated monitoring framework is not merely a technological proposal, but a strategic necessity to bridge the gap between high-level regulatory goals and local operational efficiency. By transforming raw data into actionable intelligence, such a system can optimize resource allocation, minimize environmental risks, as evidenced by recent ecological disruptions in the Piracicaba River, and support evidence-based decision-making for sustainable water governance within the PCJ Basin.

1.5 Work Structure

The work organization follows a structured scientific approach, where each chapter contributes to building a comprehensive understanding of intelligent water monitoring systems and their application in river basins.

Introduction contextualizes the global challenges related to water scarcity, pollution, and climate variability, emphasizing the increasing need for continuous and efficient monitoring of water bodies, and defining the research problem within the PCJ River Basins, highlighting gaps in current monitoring systems, particularly the lack of integrated data analysis, water quality indicators, and predictive capabilities.

Theoretical Framework section provides the conceptual and technological foundation of the study by reviewing key domains such as IoT, Big Data, AI, ML, Cloud Computing, and Geographical Information Systems (GIS). It also explores WQIs, sensing technologies, remote sensing, UAV applications, and MPC detection methods. The purpose is to consolidate current scientific knowledge and identify suitable tools and techniques for monitoring water systems, supporting the integration of multi-source data for environmental analysis.

Methodology adopts a qualitative and applied research approach, focusing on the investigation of feasible monitoring solutions for the PCJ basins. It is based on an extensive literature review using Scopus and Web of Science databases, combined with the analysis of technical and institutional documents. The section details how data sources, sensing technologies, and analytical methods were selected and organized to support the development of a proposed monitoring architecture and decision-support framework.

Results and Discussion presents and analyzes the proposed solution, including a high-level architecture that integrates IoT sensors, satellite data, historical datasets, and cloud-based processing. It evaluates communication infrastructure, sensor deployment strategies, and the feasibility of combining different monitoring techniques. The discussion also addresses limitations, challenges, and opportunities, such as data integration complexity, model calibration, and the need for reliable real-time systems to support decision-making.

Conclusions synthesize the main findings, emphasizing the necessity of an integrated and scalable water monitoring system, highlighting how combining technologies such as IoT, remote sensing, and AI can significantly improve water quality assessment and flood prediction. It reinforces the importance of data-driven decision support systems and identifies both the benefits and constraints of the proposed architecture, including technical and operational challenges.

Finally, it proposes practical recommendations for implementation, including strategic sensor placement, expansion of monitored WQIs, adoption of emerging technologies for MPC detection, and integration of machine learning for predictive analytics. It also stresses the importance of stakeholder engagement, policy alignment, and system scalability, ensuring that the proposed framework can be sustained and replicated in other river basins.

2 THEORETICAL FRAMEWORK

In this chapter, technology and techniques which can provide important foundation for analyzing collected data from water bodies are presented, particularly: sensors, remote sensing, telecommunication and computing infrastructure, water quality indicators, pollution identification techniques resulting from plastic and microplastic.

Considering that sensors will require transmitting a large volume of information, these devices will convey data using IoT – term coined by Kevin Ashton in 1999:

> [...] The Internet of Things (IoT) is a framework in which all things have a representation and a presence in the Internet. More specifically, the Internet of Things aims at offering new applications and services bridging the physical and virtual worlds, in which Machine-to-Machine (M2M) communications represents the baseline communication that enables the interactions between Things and applications in the cloud. [...]

Collected data would be later uploaded to a database to be processed and presented in the form of a dashboard of indicators. This transition from raw data to visual analytics is essential for transforming complex environmental variables into actionable insights, allowing for a more agile and evidence-based response to hydrological changes.

Large volumes of data will require special techniques best known as Big Data. In general, this term refers to the large amount of data that is increasingly available due to technological evolution, for example: data collected by sensors, facial recognition and use of social networks, normally characterized by volume, speed and variety, however, there is more to take into account: veracity, complexity and unstructuredness (De Mauro; Greco; Grimaldi, 2015).

Processing large amounts of data will need appropriate infrastructure that:

> […] requires debates on the cost-benefit involved in mining, with the purpose of creating value and innovation in various businesses. Innovative ways of processing information for greater visibility and decision-making are also becoming concerns for researchers on the subject […] (Mazzieri; Soares, 2016)

Therefore, it is important to think about the infrastructure as well as the composition of the specialized professional teams that will be necessary to enable pre-processing, transformation, data mining and interpretation or evaluation (Tsai et al., 2015).

AI is a branch of Computer Science focused on creating systems capable of performing tasks that typically require human intelligence. These tasks include reasoning, learning, problem-solving, perception, and language understanding. AI systems are designed to interpret

external data, learn from it, and utilize these learnings to achieve specific objectives through flexible adaptation (Stryker; Kavlakoglu, 2024).

The evolution of AI has led to the creation of systems that can process vast amounts of data, recognize patterns, and make decisions with minimal human intervention. These advancements have been facilitated by improvements in computational power, algorithmic development, and the availability of large datasets (Minh et al., 2022).

ML appears as a branch of AI focused on the development of algorithms that allow systems to automatically improve their performance on tasks through experience, typically by identifying patterns in data without being explicitly programmed. ML is characterized by its use of statistical methods to infer rules from data, thereby enabling predictions or classifications based on new data inputs (Alpaydin, 2014; Murphy, 2012).

ML can be categorized into several types, including supervised learning (learning from labeled data), unsupervised learning (discovering patterns in unlabeled data), and reinforcement learning (learning through reward-based feedback). The efficacy of a ML model is often measured by its accuracy, precision, and generalizability on previously unseen data (Goodfellow; Bengio; Courville, 2016).

Cloud Computing appears as a solution for storing and processing data in large volumes associated with sophisticated statistical processing and AI, since it is likely that the already available on-site infrastructures are insufficient and lack all the necessary analysis tools, thus Cloud Computing may offer a:

> [...] computing model that allows the end user to access a large number of applications and services anywhere and regardless of the platform, simply by having a terminal connected to the “cloud” (Pedrosa; Nogueira, 2011).

There are clearly important financial issues that need to be addressed, and in addition to data security, there are factors related to the training and preparation of human resources to deal with this ecosystem (Chaves; Alexandre De Souza; Corrigida, 2011). Therefore, covering these non-technical barriers is as critical as the technological deployment itself to ensure the long-term viability of the monitoring infrastructure.

It also is important to consider GIS, which are frameworks that integrate data, hardware, software, and procedural methods to capture, store, manipulate, analyze, and display geospatial data. GIS technology is used across diverse fields such as environmental science, urban planning, and transportation to understand spatial relationships and patterns. GIS functions by

layering various types of data (such as topography, demographic information, and infrastructure) onto maps, providing insights into geographic patterns and enabling decision-making based on spatial data (Longley et al., 2015; Mcdonnell, 1998).

ML and Data Fusion Techniques (DFT) can also offer valid alternatives, such as Deep Learning (DL) models such as LSTM, as well as hybrid techniques like LSTM-GWO-FSO are used for predicting water quality parameters based on historical satellite data and in situ measurements. These models are particularly valuable for forecasting water quality under pollution stress and complex environmental conditions (Perumal et al. 2023).

Finally, empirical and semi-empirical models link spectral reflectance data from remote sensing with water quality parameters like chlorophyll-a concentration, and transparency. They have been developed based on data from platforms like Landsat and Sentinel, enabling both qualitative and quantitative assessments of water quality (Zheng et al. 2024).

2.1 Water Quality Indicators

In Brazil, water quality is assessed using a combination of physical, chemical, and biological indicators (Moretto et al. 2012) – primary indicators include:

- *Ph.* Measures the acidity or alkalinity of water, influencing chemical reactions and biological processes.
- *Dissolved Oxygen (DO).* Indicates the amount of oxygen available for aquatic life; low levels can harm organisms.
- *Biochemical Oxygen Demand (BOD).* Reflects the amount of oxygen required by microorganisms to decompose organic matter; high levels suggest organic pollution.
- *Chemical Oxygen Demand (COD)*. Measures the total quantity of oxygen required to oxidize both organic and inorganic substances in water.
- *Total Suspended Solids (TSS).* Indicates the concentration of suspended particles, affecting water clarity and quality.
- *Total Dissolved Solids (TDS).* Represents the total concentration of dissolved substances, impacting water taste and suitability for consumption.

- *Turbidity.* Measures water clarity; high turbidity can reduce light penetration and affect aquatic ecosystems.
- *Temperature.* Affects chemical reactions and biological activities; significant changes can disrupt aquatic life.
- *Nitrate (NO_3).* High concentrations can lead to eutrophication and pose health risks to humans and animals.
- *Phosphate (PO_4).* Elevated levels can cause algal blooms, leading to oxygen depletion in water bodies.
- *Ammonia (NH_3).* Toxic to aquatic organisms; often originates from agricultural runoff and wastewater discharge.
- *Total Coliforms and Escherichia Coli.* Indicators of fecal contamination; their presence suggests potential pathogenic microorganisms.
- *Chloride (Cl).* High levels can indicate pollution from industrial or agricultural sources.
- *Sulfate (SO_4).* Elevated concentrations can affect water taste and may indicate industrial pollution.
- *Hardness (Calcium and Magnesium Ions).* Affects water's suitability for domestic and industrial use; high hardness can cause scaling.
- *Alkalinity.* Measures water's capacity to neutralize acids, providing insight into its buffering capacity.
- *Electrical Conductivity.* Indicates the water's ability to conduct electricity, correlating with ion concentration.
- *Total Phosphorus.* High levels can contribute to eutrophication and algal blooms.
- *Total Nitrogen.* Encompasses all forms of nitrogen; elevated levels can lead to nutrient pollution.
- *Heavy Metals (e.g., Lead, Mercury, Cadmium).* Toxic even at low concentrations; their presence indicates industrial or agricultural contamination.

2.2 Sensing Technologies

There has been a significant evolution in water sensor technology and use of satellite data – a few sensor cases are presented in Table 1.

Table 1: Sensor technology and use cases

Use case	Description	Reference
Camera Sensor for Contamination Detection	Detect contaminants like floating debris and algae, offering real-time image analysis to identify pollutants based on color and shape, making. Suitable for visually observable contamination in water bodies like lakes and rivers.	Wang et al. (2019)
Biosensors and Spectroscopy for Contaminant Detection	Optical and electrochemical biosensors and spectroscopic techniques for detecting both chemical and biological contaminants in water, sensitive to pathogens.	Zulkifli; Rahim; Lau (2018)
3D-Printed, Open-Source Water Quality Sensor Platform	A customizable platform that integrates turbidity, Total Dissolved Solids (TDS), and temperature sensors, using 3D-printed housing and open-source electronics, ideal for research and low-cost deployment in varied environments.	Kinar; Brinkmann (2021)
Early Warning Systems with Multi-sensor Arrays	For contamination events, this early warning system uses multiple water quality sensors to detect contaminants like glyphosate. The system's design emphasizes rapid detection by combining sensor outputs, achieving high accuracy in under five minutes.	Che; Liu; Smith (2015)
Remote Sensing for Surface Water Quality Monitoring	Remote sensing approaches track water quality indicators supporting large-scale monitoring of surface water, ideal for assessing environmental impacts over time and across wide regions.	Zheng et al. (2024)
Low-Cost Sensor Integration with Satellite Data	Low-cost sensors are combined with Sentinel-2 data to enhance temporal and spatial data coverage, facilitating community-centered monitoring initiatives. This approach enables calibration and validation of satellite models, making water quality monitoring more accessible and adaptive to local conditions.	Steinbach et al. (2024)

Source: author, 2026

Particularly, as for optical, thermal, microwave, and radar remote sensing, the following satellites would provide valuable information:

- *GRACE Satellite.* This satellite uses gravity measurements to estimate terrestrial water storage changes, crucial for understanding regional and global water balance. It supports

assessments of groundwater levels and drought monitoring by detecting changes in mass related to water (Chawla; Karthikeyan; Mishra, 2020).

- *Landsat Series.* These satellites are frequently employed for water quality parameters like chlorophyll-a, turbidity, and total suspended solids. Optical sensors in the visible to near-infrared range are used to detect these parameters, with Landsat data providing insights into changes in water quality and ecosystem health (Chawla; Karthikeyan; Mishra, 2020; Zheng et al., 2024).

- *MODIS and other high-resolution satellites.* These are used for continuous, large-scale monitoring of surface water dynamics and water quality parameters (e.g., total suspended matter, transparency) due to their high temporal resolution, which is useful for real-time monitoring (Zheng et al. 2024).

- *SAR (Synthetic Aperture Radar).* Radar satellites like Sentinel-1 are employed to monitor water quantity in rivers and lakes, especially during cloudy conditions where optical sensors might be limited. SAR data are beneficial for flood monitoring due to their capability to penetrate cloud cover and provide consistent observations (Zulkifli; Rahim; Lau, 2018).

- *Sentinel-2.* Used extensively for water quality monitoring in wetlands and small reservoirs, with the multispectral instrument allowing for high-resolution data. Techniques for turbidity and chlorophyll-a measurements involve bio-optical models and band combinations specific to Sentinel-2 (Steinbach et al. 2024).

2.3 Plastics and Microplastic Detection

Current satellite technology cannot directly detect riverine MPC with sufficient accuracy. However, indirect detection through satellite-derived Suspended Sediment Concentration (SSC)[2] shows high potential. Integrating optical remote sensing, ML, and hydrological proxies is presently the most feasible pathway for estimating MPC in rivers using satellites, since the spectral signature of MPCs in water is weak, often indistinguishable from

[2] SSC is the concentration of fine solid particles (such as clay, silt, and fine sand) that are transported within the water column due to turbulence and flow dynamics (usually increased during flood events).

noise due to their low concentrations and subpixel-scale presence (Mohsen; Kovács; Kiss, 2023).

Traditional analysis usually occurs at specialized laboratories, being time-consuming and expensive. AI-assisted visual sensing is a promising frontier in microplastic detection, offering speed, automation, and scalability. Integration of advanced imaging with AI holds potential to have an important impact in environmental monitoring (Hasan et al. 2024).

There are initiatives in developing a device for real-time, *in-situ* detection and monitoring of microplastics in aquatic environments using IoT architecture and intelligent computing models. Such a device would represent a significant step toward intelligent, scalable, and autonomous systems for monitoring microplastic pollution in water, merging advances in IoT, multimodal imaging, and AI to address the urgent need for efficient environmental sensing solutions (Chaczko et al. 2018).

Multiple cutting-edge technologies are being explored for plastic and microplastic detection, each with unique strengths summarized in Table 2.

Table 2: Plastic and microplastic detection

Type	Description	Comments	Reference(s)
Biosensors	Use biological recognition elements integrated with a transducer for detecting microplastics and associated toxins	High specificity, sensitivity, potential for in situ and real-time detection. Stability and reproducibility challenges due to biological material fragility.	Johnpaul et al. (2024); Popenda et al. (2024)
IoT and AI-Based Systems	Combines IoT devices (camera, Global Positioning System [GPS], wireless modules) with AI (Mask R-CNN and COCO-trained vision models) to detect macro-plastics.	Designed for scalability, open-source development, and integration with autonomous trash collection robots. Aims to identify floating macro-plastic sources and optimize trash removal strategies.	Kelly et al. (2023)
Portable Optical Detection	Adapted cell-counting flow chambers with microscopy and imaging software. Videos analyzed to quantify and size microplastics	Optical detection was favored for being portable, real-time, low-cost, and moderately accurate compared to lab-intensive methods.	Childers et al. (2023)
Microfluidic Sensors	Real-time in situ detection of microplastics and emerging contaminants using compact “lab-on-chip” systems	Miniaturization, low reagent use, portability, automation. Sensor fouling, fabrication complexity, and achieving consistent detection sensitivity for nano-plastics.	Pavanelli; Bigi (2005)

Type	Description	Comments	Reference(s)
Remote Sensing (aerial and satellite detection)	Three main approaches: spectral analysis, water surface roughness, and indirect proxies (e.g., associated turbidity or organic matter). Best potential lies in drone-based hyperspectral imaging for surface detection	Effective mainly for floating plastics or high concentrations; poor resolution for submerged or nanoscale microplastics.	Chabot; Marteinson (2024)
Magnetic Sensors	Magnetic nanomaterials (e.g., Fe_3O_4 nanoparticles) used to capture and quantify microplastics and associated heavy metals	Reusability, high surface area, good selectivity, and integration with electrochemical or colorimetric systems	Hojjati-Najafabadi et al. (2022)

Source: author, 2026

Important to note that the technologies presented in Table 2 were researched in China, Europe and the USA.

2.4 Flood Monitoring

Flood control techniques, presented as a special case in the context of monitoring and early warning systems, focusing on Wireless Sensor Network (WSN) and systems based on IoT, can be seen in Table 3.

Table 3: Flood monitoring techniques

Use case	Description	References
WSN for real-time data collection	A WSN approach involves deploying multiple sensor nodes in flood-prone areas to monitor variables such as water level, temperature, rainfall, and humidity. These nodes can communicate data to centralized or distributed systems, which help in assessing and predicting flood risks.	Nalavade et al. (2019); Seal (2012)
IoT-based early warning systems	IoT technologies enhance WSNs by enabling remote monitoring and real-time data transfer through internet connectivity. This setup allows for real-time analysis and visualization of data, which can trigger alerts if parameters reach critical levels.	Mendoza-Cano et al. (2021)
Hybrid ML Models for flood prediction	ML models, often integrated with IoT, analyze environmental data trends to predict flood risks. Techniques such as Support Vector Machines and DL are employed to enhance prediction accuracy. These models can process complex data, including satellite imagery and historical weather patterns, to forecast flood events.	Kumari et al. (2020); Siddique et al. (2023)

Use case	Description	References
Ultrasonic and rain sensors for water level and rainfall measurement	Specific sensors, like ultrasonic sensors for water level measurement and rain sensors for rainfall intensity, are used to gauge flood indicators. These sensors, linked to IoT systems, provide real-time measurements that aid quick decision-making by authorities. Data from such sensors help automate response actions, such as sending alerts to nearby populations or adjusting infrastructure settings to control water flow.	Nalavade; Shingate; Patil (2019)
Simulation and predictive modeling for flood scenarios	Simulations of potential flood scenarios using historical data and predictive algorithms allow for proactive planning. This predictive modeling approach is effective for areas where flash floods are common due to runoff or overflowing rivers.	Kumari et al. (2020)
Automated alert systems and public notifications	Flood alert systems, often incorporating GSM or internet-based notifications, inform local populations of impending floods. These alerts can be sent via SMS, web notifications, or mobile applications. Additionally, control systems may regulate barriers or gates to manage water flow, helping to prevent overflows and reduce flood impact.	Siddique; Ahmed; Husain (2023)

Source: author, 2026

It is worthwhile mentioning that the technologies presented in Table 3 were researched in China, Europe and the USA.

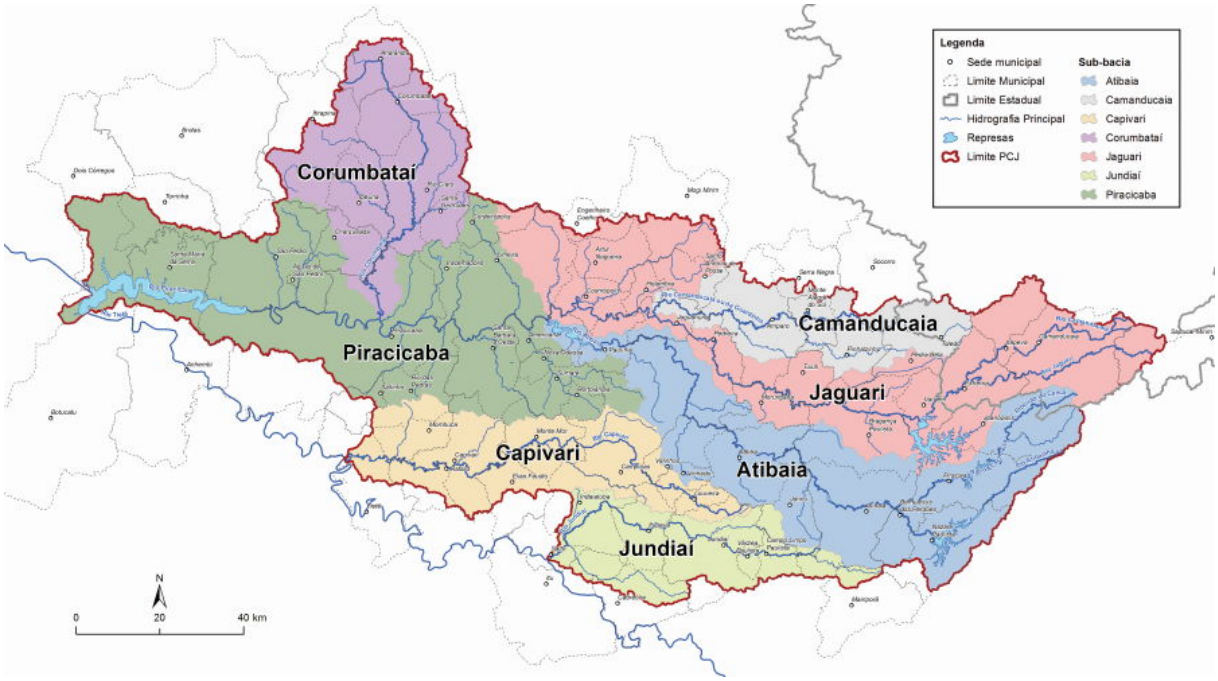
3 METHODOLOGY

Regarding the methodological approach, this study is predominantly qualitative, "since it is not concerned with numerical representation, but rather with deepening the understanding of a social group, an organization, etc., […] seeking to produce new information" (Gerhardt; Silveira, 2009).

It transcends the basic research towards applied research, since it pursues generating knowledge for practical application, aimed at solving specific problems, and involves local truths and interests (Gerhardt; Silveira, 2009).

This work focus on investigating monitoring implementation alternatives in the PCJ Region (see Figure 2) that could be used by the PCJ Agency, as to propose a model based on a combination of sources (data from satellites, locally placed new sensors and/or enhance the currently available), and use techniques such as data science and AI, such that information would be available in the form of a modern DSS.

Figure 2: PCJ Region



Source: PCJ River Basin Agency (2025)

As a starting point for this work, a bibliography of 103 articles was provided. This set was produced by a *Research Group*, formed by the *Pontifical Catholic University of Campinas* partnered with the *Piracicaba, Capivari and Jundiaí River Basin Agency Foundation*, and the *School of Engineering of São Carlos, State University of São Paulo* – this initiative is sponsored by *São Paulo Research Foundation* (FAPESP).

Additionally, articles searched in Scopus Database covering specific topics were included: Artificial Intelligence (4 articles), Big Data (4), Cloud Computing (2), Decision Support Systems (3), Deep Learning (1), Digital Technology (1), Geographical Information Systems (3), Internet of Things (6), Machine Learning (2), Microplastic (72), Remote Sensing (13), Unmanned Aerial Vehicle (5), and Water Quality Index (1) – reaching a total of 117 papers.

From the 220 resulting set, material was prioritized, based on its *content*, *scope*, and *direct relation* to this work (see Table 4 for an example): 51 articles were found to be *most relevant*, 10 *relevant*, and 9 *important*. Articles classified as 'not relevant' were excluded from the final synthesis to ensure the framework is focused on the specific technological and geographical requirements of the PCJ region). This resulted in a final set of 70 articles.

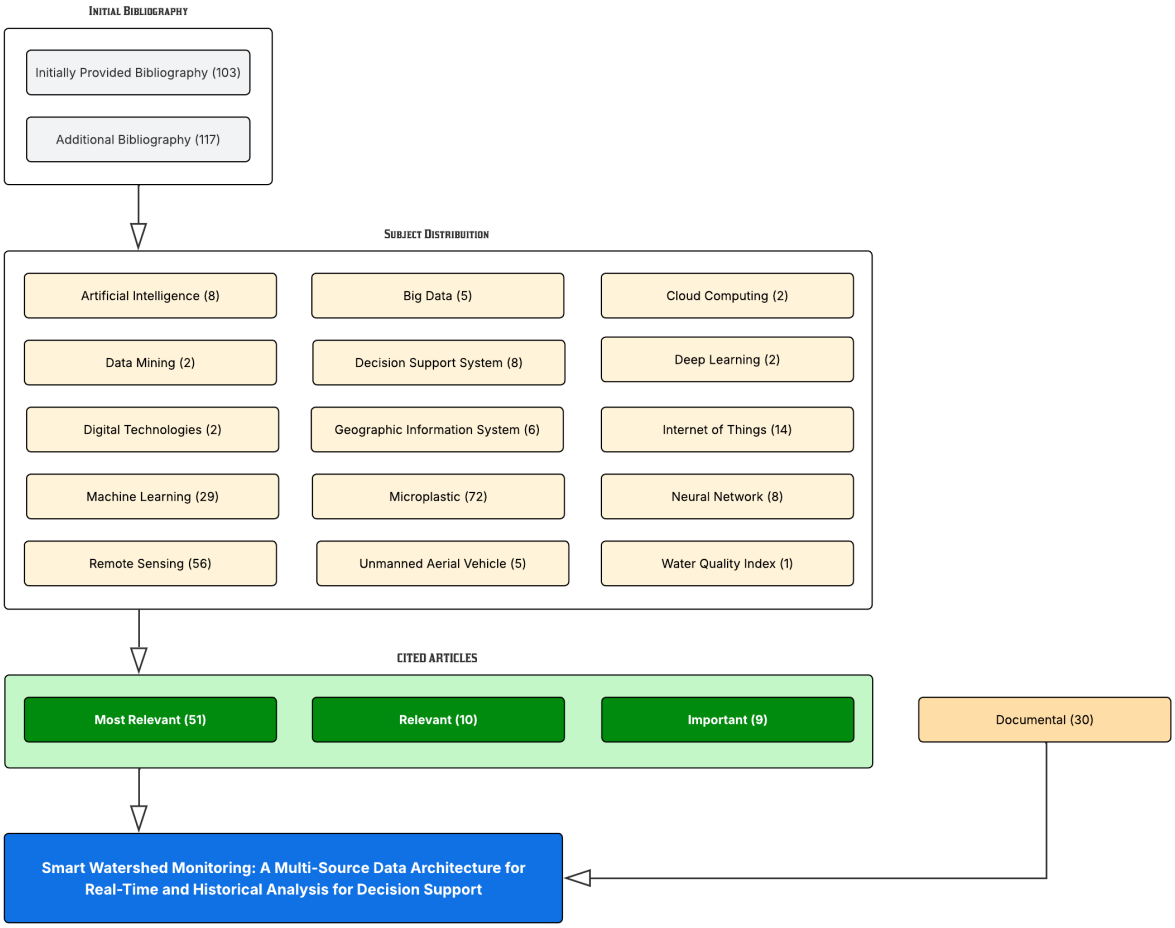
Table 4: Example of classification of articles

Subject	**Example**	**Justification**
Artificial Intelligence	Most Relevant	River monitoring using image-based techniques.
Big Data	Most Relevant	Real-time IoT architecture for water management.
Cloud Computing	Most Relevant	Intrinsic risks related to Cloud Computing.
Decision Support System	Important	Reviewing AI-based DSS in modern industries.
Geographical Information System	Most Relevant	Combination of techniques related to detection of flooding risks.
Internet of Things	Most Relevant	Measuring special-temporal river flow regularities.
Machine Learning	Not Relevant	Water leakage detection
Microplastic	Relevant	Biosensors in environmental analysis
Remote Sensing	Not Relevant	Remote sensing related to groundwater.
Unmanned Aerial Vehicle	Most Relevant	Water quality mapping.

Source: author, 2026

Documental sources (30) were added, particularly related to the Brazilian Government, newspapers, industries and research organizations – giving a total of 98 (Figure 3 depicts the organization strategy).

Figure 3: Bibliography organization strategy



Source: author, 2026

The methodological procedures were organized into three main phases:

1. *Exploratory Phase.* Systematic literature review and document analysis to identify gaps in the PCJ basin monitoring;
2. *Technical Feasibility Analysis.* Survey of sensor technologies, communication infrastructure, and cloud computing architectures;
3. *Model Proposal.* Design of the theoretical framework and selection of a pilot location for potential deployment.

This led to organizing the resulting set of articles as shown in Table 5 – important to notice that articles were researched on Scopus and/or Web of Science databases.

Table 5: Article subject distribution

Subject	**Quantity**
Artificial Intelligence	3
Big Data	5
Cloud Computing	2
Decision Support system	4
Deep Learning	1
Geographic Information System	5
Internet of Things	7
Machine Learning	4
Microplastic	15
Remote Sensing	19
Unmanned Aerial Vehicle	4
Water Quality Index	1

Source: author, 2026

This organization aligns with the aforementioned phases and was conceived considering the core answer sought by this work, which is to provide data collection methods and a modern valid tool to analyze this data. In this case, technical criteria indicate that selecting the appropriate sensing techniques functioning as data sources must be correctly identified.

It is important to note that combining collected data with satellite feeds would provide much richer information. This integration would enable tools not only to analyze water quality

but also to monitor flood events. *In-situ* analysis and UAVs were also researched to create a foundation for combination alternatives.

Selecting the feasible sensor types accounting for availability were the next steps, so additional information in the form of available sensor types and models were researched in the market, as to corroborate the feasibility of the proposed solution.

Collecting data from such diverse sources would naturally require modern techniques and architecture to store and analyze data, indicating that a cloud computing environment would be adequate for Big Data and Data Science (where historical data could be uploaded), especially because it would inherently support developing a sandbox analysis.

Subsequent issues to be equated would be the availability of communication infrastructure to connect locally placed sensors to this environment, as well as the feasibility of installing devices out in the open.

In summary, a modern framework to analyze water bodies would be created by integrating multiple data sources acquired by appropriate sensing techniques.

Chapter 4 presents a) a theoretical model of a high-level data collection architecture; b) availability of telecommunication infrastructure; c) a brief discussion on sensor types; d) sensor types and models available in the market; and, as an example, e) a specific location in the PCJ Area where a sensor could be deployed.

4 RESULTS AND DISCUSSION

The PCJ Area, characterized by a large urban agglomeration and industrial presence, faces recurring water contamination from industrial pollution, illegal sewage, and agricultural runoff, as previously mentioned. Furthermore, population growth, coupled with increasingly irregular rainfall patterns due to climate change, presents a significant and growing risk of unexpected flooding.

The analysis involves numerous challenges, particularly: defining the best sensing method or combination of methods, and accounting for variables like geography (e.g., UAV, satellite, and/or strategically placed sensors), geography, topology, rain distribution, water flow, etc.

PCJ Agency collects an immense quantity of data (Ministry of National Integration and Regional Development, 2025), however for analysis performed by external actors it can only be downloaded or accessed by spreadsheets, meaning that any form of reporting or deep analysis that combines external data (such as weather and pollution data) presents difficulties. This data forms a rich set of historical information to which access may be hindered by intrinsic complexities of manual manipulation, however it can be uploaded to a cloud provider and made available for deeper analysis.

Techniques related to remote sensing encompass optical sensors through accessing data from Landsat, Sentinel-2 and MODIS, widely available and presenting global coverage (Adjovu et al., 2023; Chawla; Karthikeyan; Mishra, 2020; Cretaux et al., 2023; Nagaraj; Kumar, 2024).

Radar based sensors are most useful in all types of weather including cloudy conditions, complementing optical data (Do et al., 2023; Zheng et al., 2024).

When integrated with GIS, remote sensing provides a robust platform for analyzing spatial and temporal trends in water quality possibly enhancing decision-making capabilities (Habeeb; Weli, 2021; Nagaraj; Kumar, 2024).

There are challenges and limitations, though, related to ML and analytical models that require significant computational resources and must rely on good ground data. Field calibration is necessary for *in-situ* data when validating estimates derived from remote sensing measurements.

Finally, UAVs have proven adequate for specific use cases, such as water sampling (Lariosa et al., 2024)) and have been proposed as a means to validate satellite data for water bodies (Wasehun; Hashemi Beni; Di Vittorio, 2024)). While modern UAVs can even operate in cloudy weather (De Keukelaere et al., 2023), unlike traditional small-scale sampling (Sibanda et al., 2021), their practicality is limited by scale. Covering the PCJ vast area of 15,000 square kilometers (Agência das Bacias PCJ, 2025) using only UAVs would be impractical.

Sensors can be combined with other techniques such as satellite to collect, for example, pH, turbidity, and conductivity (Table 6), offering rapid detection of contaminants, however, may present high setup costs and potential false positives in complex environments. Since communication is IoT based, they are highly dependent on network coverage (Che; Liu; Smith, 2015; Mendoza-Cano et al., 2021).

Table 6: Indicators that are feasible to be collected

Target	Notes	References
Chemical and biological oxygen demand	Indicators of organic pollutants, essential for assessing water pollution levels in urban environments.	Do et al. (2023)
Chlorine	Can be measured with amperometric or colorimetric sensors (standard requirements in WMSs).	Kinar & Brinkmann (2021); Lambrou et al. (2014)
Chlorophill-a	A critical indicator of phytoplankton biomass widely monitored using remote sensing technologies. Chlorophyll-a data is derived using optical sensors like Sentinel-2 and Landsat series, enabling effective tracking of eutrophication	Adjovu et al. (2023); Cretaux et al. (2023); Steinbach et al. (2024); Zheng et al. (2024)
Colored dissolved organic matter	Tracks dissolved organic compounds and are essential for water quality monitoring in estuarine and coastal zones. Remote sensing platforms like MODIS and Sentinel-2 provide spatially distributed data.	Adjovu et al. (2023); Cretaux et al. (2023); Zheng et al. (2024)
Cryptosporidium and giardia	Requires specialized biosensors, typically fluorescence-based, which are feasible but more expensive and less common in standard setups	Zulkifli; Rahim; Lau (2018)
Dissolved oxygen	Optical or electrochemical sensors applied to real-time monitoring.	Kinar; Brinkmann (2021)
Electrical conductivity	Sensors are effective for assessing dissolved ionic content.	Kinar & Brinkmann (2021); Lambrou et al. (2014)
Escherichia coli	Advanced biosensors and spectroscopic systems are effective in detecting microbiological contaminants.	Lambrou et al. (2014); Zulkifli; Rahim; Lau (2018)
Heavy metals (e.g. arsenic, lead, cadmium)	Using advanced technology such as biosensors, spectroscopic techniques or electrochemical sensors) – more complex, however achievable for continuous monitoring.	Lambrou et al. (2014); Zulkifli et al. (2018)
Nitrates and phosphates	Can be detected using spectrophotometric or ion-selective electrodes (requiring more advanced technology).	Moretto et al. (2012)
Oxidation-reduction potential	Sensors are commonly used align with pH sensors	Lambrou et al. (2014)
pH	pH sensors are widely available and integrated into most WMSs.	Kinar; Brinkmann (2021)

Target	Notes	References
Pressure and temperature	Atmospheric pressure and temperature changes are used as auxiliary indicators of weather conditions that might lead to flooding.	Kumari et al. (2020)
Rainfall intensity	Continuous rainfall measurement is used to predict flooding. Rainfall exceeding the drainage capacity is a key trigger (sensors can be integrated into IoT systems for real-time monitoring).	Kumari et al. (2020); Nalavade et al. (2019)
Riverbank overflow	Defined thresholds of river capacity are used to determine when water might breach the banks and lead to flooding	Korjenić et al. (2021); Siddique et al. (2023)
Secchi disk depth	A traditional parameter now integrated with remote sensing for visibility and water transparency analysis.	Adjovu et al. (2023); Chawla et al. (2020)
Soil saturation	Excess water from heavy rainfall or melting snow increases runoff and contributes to floods.	Korjenić et al. (2021)
Temperature	Temperature sensors are straightforward to integrate into most WMSs through IoT.	Kinar; Brinkmann (2021)
Total dissolved solids	Conductivity sensors are often used as a proxy for these measurements.	Kinar; Brinkmann (2021)
Total suspended solids	Indicates sediment and particulate matter concentrations in water. Remote sensing uses spectral reflectance to estimate these values.	Adjovu et al. (2023); Cretaux et al. (2023); Wu et al. (2023)
Turbidity	Optical turbidity sensors measure scattering of light caused by suspended particles.	Kinar & Brinkmann (2021); Lambrou et al. (2014); Steinbach et al. (2024); Zheng et al. (2024)
Water level	Measured using ultrasonic sensors or other technologies to detect the height of water (threshold levels are used to trigger warnings for potential floods).	Kumari et al. (2020); Seal (2012)

Source: author, 2026

Several factors must be considered when defining sensor placement spots, such as geography, topography, rainfall distribution for flood prevention (Seal, 2012). On the other hand, detecting water contaminants may present difficulties when covering such large area as the PCJ compared to Water Distribution Systems (WDSs) (Shahra; Wu, 2020).

An initiative from San Diego University proves feasibility of real-time water quality reporting: "[…] encased within a submerged platform, the sensors emit a light beam that strikes water molecules. Organic compounds in the wastewater absorb the light and emit a fluorescent signal, which is detected by the sensors" (Ristine, 2024).

Emerging technology known as microfluidic offers precise manipulation and analysis of small amounts of fluids with volumes in the range of nanoliter to microliter. When compared to other water quality testing techniques, microfluidics is very favorable for a series of facts, such as selectivity, sensitivity, real-time monitoring, environmental friendliness, and small sample size. It has made great progress in the field of water quality testing, mainly for some water quality indicators (Table 7).

Table 7: Detection techniques for categories of pollutants

Category	**Detection techniques**
Pharmaceuticals and personal care products	Electrochemical sensors (e.g., voltammetry), optical sensors (e.g., fluorescence, colorimetric assays).
Endocrine disrupting chemicals	Often detected using biosensors integrated into microfluidic systems, utilizing aptamers or antibodies for specific binding.
Microplastic	Optical methods (e.g., fluorescence, surface plasmon resonance), conductometric and calorimetric biosensors, piezoelectric sensors for size/mass detection, use of biosensors that recognize plastic polymer surfaces or additives.
Perfluorinated compounds	Electrochemical sensors with molecularly imprinted polymers or antibody-functionalized surfaces.

Source: Zheng et al. (2024) adapted by the author

Due to the unique electromagnetic properties of MPC, which differs from those of water, a prototype was built with microfluidic technology which proves the pressing challenges of detection and monitoring water bodies, particularly the detection performance for a variety of MPCs (Wen et al. 2024).

Traditional *in-situ* sampling methods for detecting microplastics are accurate but limited by cost, labor, and spatial-temporal coverage. On the other hand, satellites offer high spatial and temporal resolution, coverage of inaccessible or hazardous areas, potential for global, repeated, and real-time monitoring. Combining satellite data with ML and DL can improve

classification accuracy by enhancing spectral contrast between plastics and other materials (Mukonza; Chiang, 2022).

4.1 Sensors Provided by Industries and Research Institutes

Dealing with remote water level monitoring Manx Technology Group (Figure 4) reports a "[…] sensor node [that] is strategically affixed to a river structure, such as a bridge, or mounted on a pole positioned near the river that requires monitoring. Connected to this node, the ultrasonic sensor is installed at a specific height above the body of water, where it continuously measures the distance between itself and the water surface" (Manx Technology Group, 2025).

Figure 4: Sensor attached to a bridge



Source: Manx Technology Group (2025)

A sensor device (Figure 5) "with the capability of sending data to long distance using GSM module […] can be deployed in remote or distant areas since it can operate independently […] but must have solar power as an energy harvester due to the high power-consuming requirement of the GSM module" (Demetillo; Japitana; Taboada, 2019).

Figure 5: Sensor node



Source: Demetillo; Japitana; Taboada (2019)

In-situ multiparameter probes house multiple sensors to continuously monitor river water quality. These instruments measure key parameters such as pH, DO, turbidity, conductivity, temperature, and nutrients (Table 8). Each sensor type has specific technical characteristics (range, accuracy, response time, durability, and operating conditions) optimized for field deployment in rivers (White Oak, 2025; YSI Inc., 2025).

Table 8: Available sensor types

Purpose	**Description**
Conductivity	Conductivity sensors measure the electrical conductance of water, which correlates with dissolved ionic content (salinity/total dissolved solids). They typically use either a 4-electrode cell or inductive (toroidal) sensor for a wide range, or a 2-electrode cell for simpler applications. In river monitoring, conductivity (often reported as specific conductance at 25 °C) helps indicate salinity changes, pollution, or mixing of water sources.
DO	Two main DO sensor technologies exist: optical (luminescent) and electrochemical (galvanic or polarographic). Optical DO sensors have become the standard for river monitoring due to their stability and low maintenance. They use a fluorescence quenching principle: a dye on a sensor cap emits light in proportion to oxygen concentration. Electrochemical DO sensors (Clark cells) consume oxygen and require stirring; these are less used now in continuous deployments.
Nitrate	Nitrate is a key nutrient parameter. Two common sensor types are used in rivers: Optical UV nitrate sensors and Ion-Selective Electrode (ISE) nitrate sensors. Optical nitrate sensors measure absorption of UV light by nitrate (often around 212 nm), sometimes using LEDs (e.g. YSI NitraLED) or lamps (e.g. Hach Nitratax). They offer continuous *in-situ* monitoring without reagents. ISE nitrate sensors use a selective membrane that develops a voltage proportional to nitrate ion activity; these are typically integrated into multiparameter sondes as a low-power option.
pH	pH sensors for field use are typically electrochemical (glass electrode) sensors that measure hydrogen-ion activity.

Purpose	Description
Phosphate (Orthophosphate)	Phosphate is typically measured as orthophosphate in water. Direct *in-situ* measurement is challenging without reagents, so most phosphate sensors are wet-chemical analyzers. These take in water, add reagents (e.g. molybdate color reagent for the phosphomolybdate blue method), and optically measure the color change. Such analyzers are often installed at river monitoring stations with a pumping system. True reagent-less phosphate probes are not yet common; an alternative in some research is an ISE for phosphate, but those have relatively poor performance. Thus, continuous phosphate monitoring usually relies on analyzers like the Hach Phosphax or OTT HydroMet's phosphate analyzer.
Temperature	Temperature in water quality probes is measured by a thermistor integrated into the probe (often within the conductivity sensor or as a separate small probe). Accurate temperature readings are critical, both as an environmental parameter and for compensating pH, DO, and conductivity measurements.
Turbidity	Turbidity sensors measure water clarity by detecting light scattering caused by suspended particles. Most are optical nephelometric sensors, shining an infrared or white light LED and measuring scattered light at 90° (Nephelometric Turbidity Units, NTU). Some sensors also estimate Total Suspended Solids (TSS) via calibration. In rivers, turbidity sensors must handle a wide range of turbidity (from clear low-NTU water to very turbid flood conditions) and resist fouling.

Source: Fondriest Environment Inc. (2025); White Oak (2025); YSI Inc. (2025), adapted by the author

When deploying these sensors in a river, one must consider environmental operating conditions: temperature (ensure equipment can handle winter freezing or summer heat), biofouling (schedule cleaning or use antifouling coatings/wipers), and hydraulic conditions (mount sensors in a location with representative flow but protected from debris). Calibration and maintenance schedules are crucial to ensure the sensors retain their stated accuracy over time; e.g. pH may need weekly calibration, DO optical caps yearly replacement, turbidity checks with standards monthly, etc., as recommended by manufacturers (Hach, 2025; YSI Inc., 2025).

An overview of the main types of sensors used in flood monitoring is presented below (Table 9).

Table 9: Flood monitoring sensors

Type	Description
Water level sensors (stage sensors)	Measure the height of the water surface in rivers, reservoirs, or floodplains. Essential for flood detection and early warning systems.
Rainfall sensors (rain gauges)	Monitor rainfall intensity and total accumulation to assess flood risk from upstream precipitation.
Flow velocity sensors	Measure the speed of water movement, often combined with level data to calculate discharge.

Type	Description
Multiparameter telemetry stations	Combine sensors (level, rainfall, flow) with data loggers and remote communication (GPRS, LoRa, satellite) for real-time alerts and monitoring.

Source: Campbell Scientific, 2025; In-Situ, 2025; OTT Hydromet, 2025, adapted by the author

Since MPC detection is a relatively new subject, Table 10 presents some companies and research institutions which have developed sensors and technologies for detecting microplastics – these solutions range from portable field devices to advanced laboratory instruments.

Table 10: Some available detection solutions in the market

Entity	Type	Description	Reference
Aquatic Sensors (USA/Canada)	Commercial	Aquatic Sensors provides environmental monitoring solutions, including digital field microscopes and sensors for water quality parameters. Their equipment can aid in the detection and analysis of microplastics in freshwater systems.	Acquatic Sensors (2025)
ASTRAL Project (EU)	R&D Initiative	The ASTRAL project has developed AI-powered sensors for detecting microplastics in aquaculture sites. These sensors utilize photonics and computer vision to monitor water samples in real-time. While initially focused on aquaculture, the technology is adaptable for riverine environments.	Crowd Helix (2025)
BOQU Instrument (China)	Commercial	BOQU Instrument specializes in water quality sensors and analyzers. While their primary focus is on parameters like pH, dissolved oxygen, and turbidity, their sensors can be integrated into systems for monitoring microplastic pollution in water bodies.	Boqu (2025)
Eyes on Plastic (ESA Project)	Integrated Monitoring Systems	The European Space Agency's "Eyes on Plastic" project combines satellite data, on-site sensors, and AI to detect and track aquatic plastic litter from local to global scales. The system has been demonstrated in various locations, including Guanabara Bay, Brazil.	The European Space Agency (2025)

Entity	Type	Description	Reference
Ocean Diagnostics (Canada)	Commercial	Ocean Diagnostics offers a suite of technologies for microplastic monitoring in freshwater and marine environments. Their solutions include the ASCENSION automated depth sampler and the SATURNA imaging system, which utilizes machine learning for particle identification. They also provide *in-situ* microplastic sensors and community science toolkits.	Ocean Diagnostics (2025)
SubCtech (Germany)	Commercial	SubCtech has developed an innovative Microplastic Sampler designed for ocean surface microplastic collection. This system operates autonomously and can be used on various vessels, making it suitable for riverine and marine environments.	Subsea Technologies (2025)
University of British Columbia (Canada)	R&D Initiative	Researchers at UBC have created a portable, low-cost device capable of detecting and quantifying microplastics in water samples. The device captures fluorescent microscopic images and uses machine learning to analyze the presence of microplastics	Burns (2024)
Woods Hole Oceanographic Institution (USA)	R&D Initiative	Is developing an impedance-based sensor for real-time detection of microplastics in various water bodies, including rivers. This technology aims to differentiate between plastic particles and biological materials in fluid flows.	Woods Hole Oceanographic Institution (2025)

Source: author, 2026

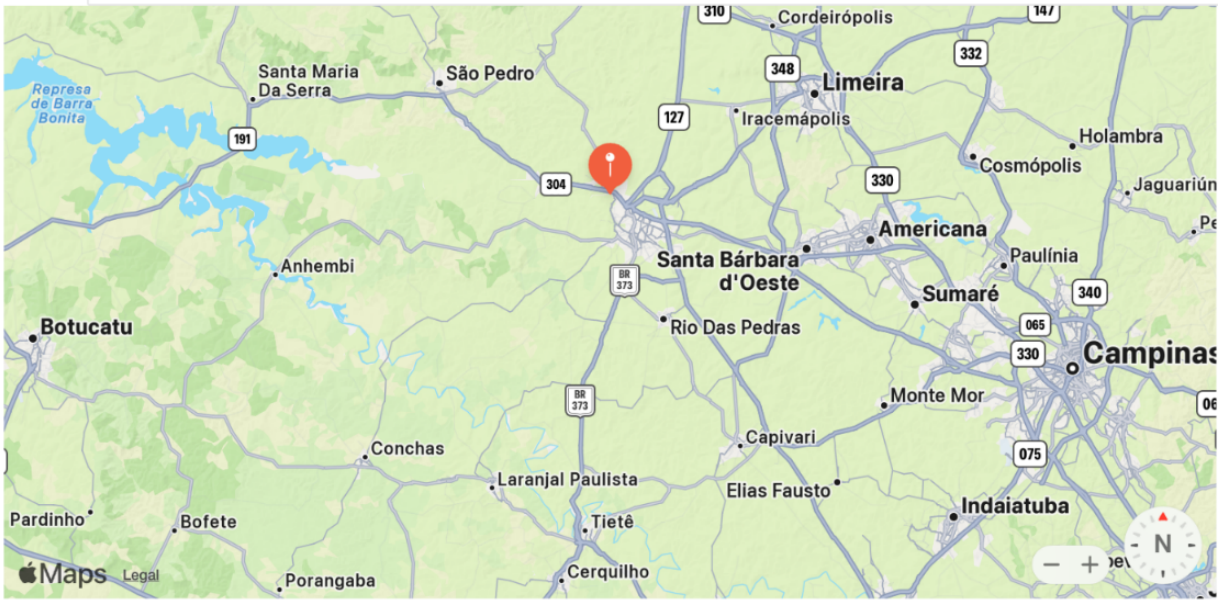
These organizations offer a range of technologies suitable for monitoring microplastic pollution in riverine environments. Depending on specific requirements such as portability, real-time analysis, and integration with existing systems, these solutions can be tailored to various monitoring needs.

4.2 Deploying a Sensor in the PCJ Area

As an example, Costa Pinto Plant (Raízen, 2025), located at the margin of Corumbataí River (which is a tributary of Piracicaba River), indicates that a sensor should be placed on the Corumbataí mouth (latitude S 22°41'20.36", longitude W 47°40'41.826”, Figure 6). This area offers several conveniences such easy access (urban area with telecommunication coverage enabling IoT communication) and has a history of pollution since it was fined in the year of

2024 for dumping vinasse in one of the tributaries of the Corumbataí River (NOVACANA, 2024).

Figure 6: Sensor location at the mouth of Corumbataí River

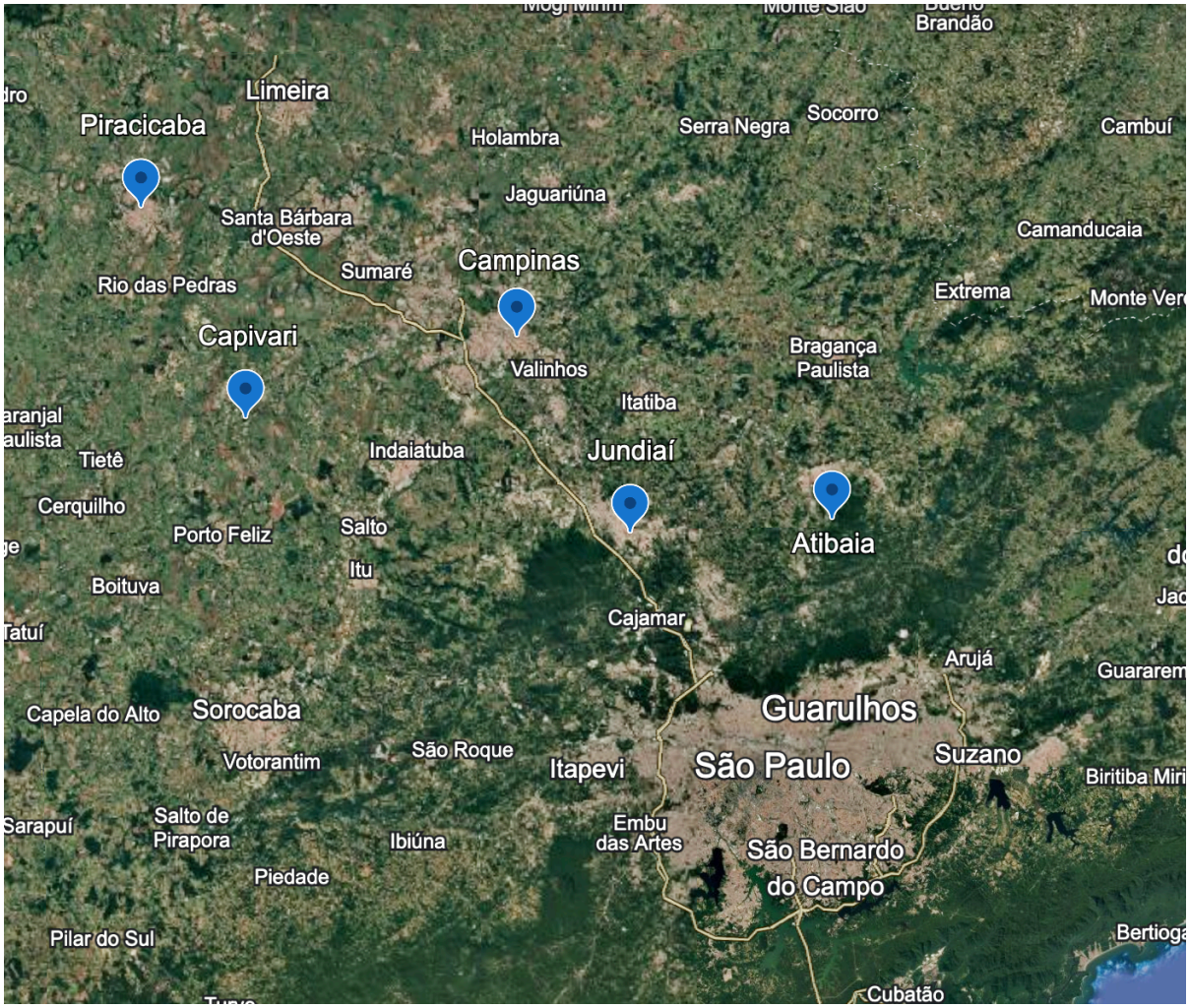


Source: GPS Coordinates Converter (2025)

For effective data collection, both sensor location and sampling frequency play an important role. While low frequencies may miss flood or pollution events, excessively short intervals require a near-real-time architecture (López-Ramirez; Aragon-Zavala, 2023).

To allow remote controlled sensors to collect data, transmission capabilities must be available. Fortunately, PCJ is located in a highly dense population area, with good telecommunication coverage – note in Figure 7 main cities are marked (Atibaia, Campinas, Capivari, Jundiaí and Piracicaba), all bathed by the rivers that make up the PCJ.

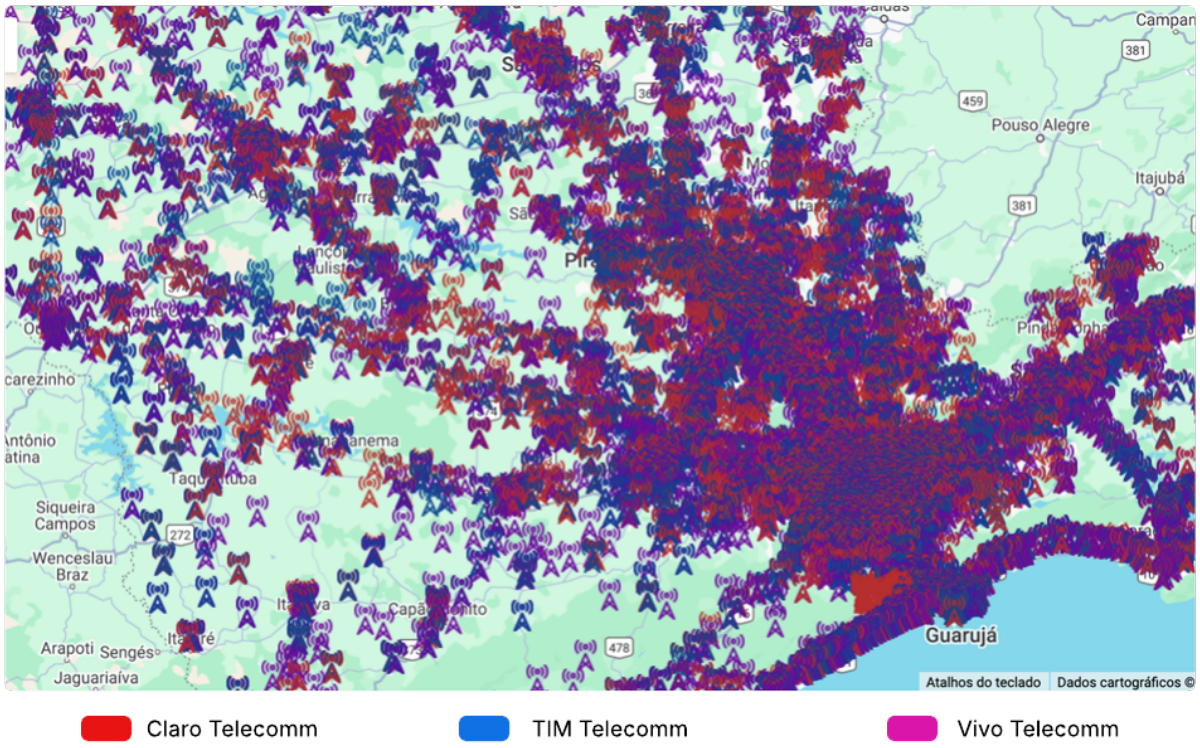
Figure 7: Main cities in the PCJ basins area



Source: Google (2025)

In São Paulo State there are 23,228 cellular antennas (Figure 8), covering main cities and roads, which offer a viable way of transmitting data collected by locally placed sensors (Conexis, 2024).

Figure 8: Cellular antenna distribution in São Paulo State (PCJ Basins equivalent area)



Source: Conexis (2024)

If cellular coverage does not suffice, currently there are companies offering communication over satellite, such as Globalstar (Globalstar, 2025) and Starlink (Starlink, 2025).

Several approaches regarding the use of technology in water network systems can be found in the literature, and key points are related to sensor location placements, real-time data acquisition, integration with GIS, use of ML techniques in the acquired data, and a proposition of a layer in the form of dashboards, however lacking in these are historical and data collected from satellite (Bharani Baanu; Jinesh Babu, 2022; Iancu; Ciolofan; Drăgoicea, 2024; López-Ramirez; Aragon-Zavala, 2023; Xu et al., 2022).

A high-level architecture proposition includes (Figure 9):

- A *cloud provider* [1] which is an organization that delivers computing resources and digital services over the internet using a shared, scalable, and virtualized infrastructure. These services enable users to provision, manage, and release resources on demand without owning or maintaining the underlying physical hardware. From a technical perspective, a cloud provider operates large-scale data centers and exposes resources through standardized service models. Cloud providers abstract physical infrastructure

through virtualization and containerization, exposing logical resources (computing nodes, storage volumes, databases, message queues) that can be orchestrated programmatically. This abstraction enables high availability, fault tolerance, geographic distribution, and integration with advanced services such as big data analytics and artificial intelligence.

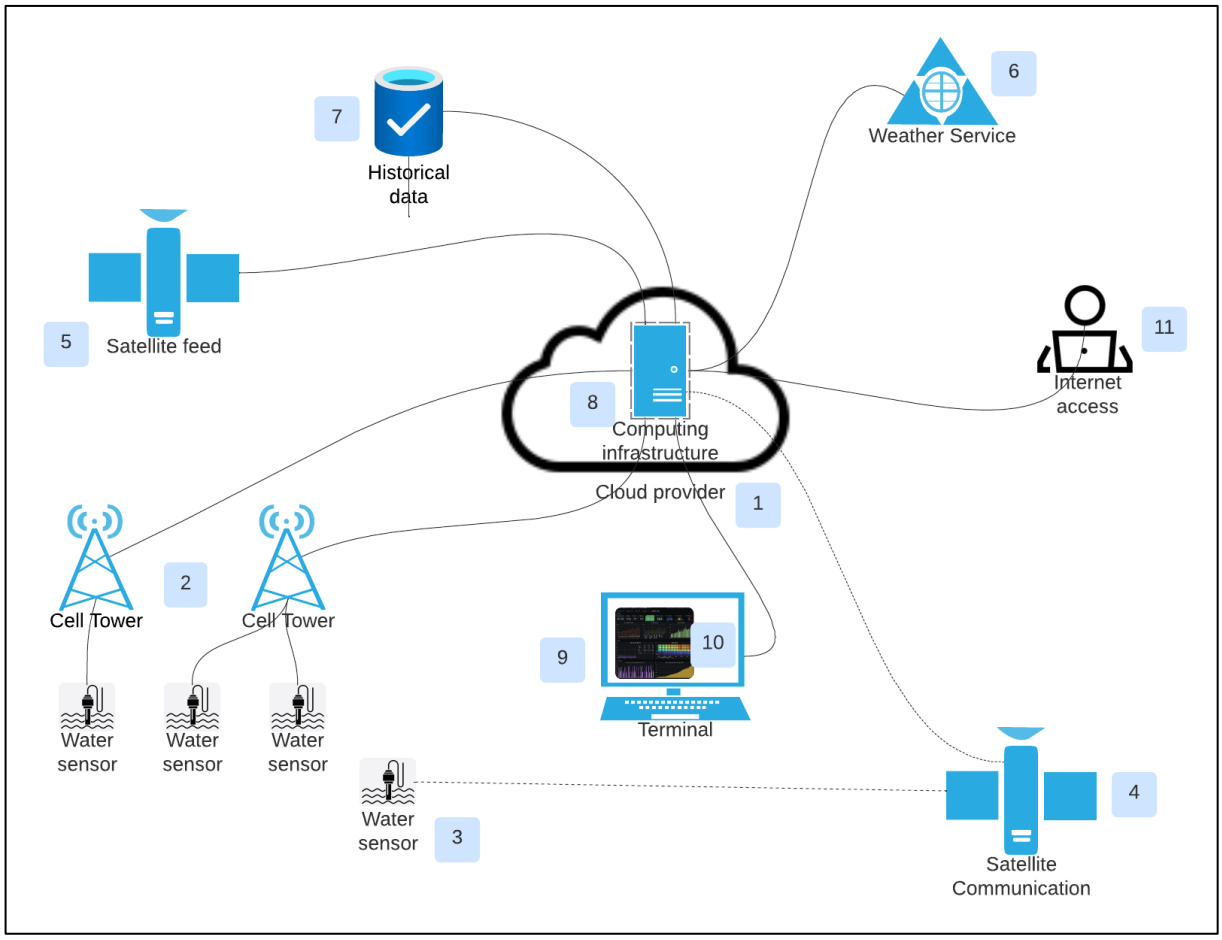
- *Locally placed sensors* [2][3] transmitting information near real-time. These sensors are connected to the available cellular network in place — eventually where coverage is not available, they will connect to a satellite telecommunication provider [4].
- *Satellite feed* [5] from Earth observation including weather in the region under scope.
- *Weather data* [6] provided from organizations and/or institutions (e.g., INMET[3] and INPE[4]).
- *Historical data* [7] available from PCJ Agency — this task is supposed to be performed just once, as to create basis for detailed analysis.
- *Computing nodes* [8] in a cloud provider these are individual computational units that execute workloads, store data, and communicate with other nodes as part of a distributed cloud infrastructure. Each node contributes processing power, memory, storage, and networking to collectively support scalable, resilient, and high-availability services. In this proposed environmental monitoring architectures, computing nodes commonly perform roles such as real-time ingestion of sensor and satellite data streams, pre-processing and quality control of raw observations, execution of ML/AI models for anomaly detection or forecasting, storage and querying of historical datasets, serving dashboards and decision-support applications.
- *Terminals* [9] as main consoles. A terminal in a cloud computing environment is a command-line interface that allows users to interact directly with cloud-based computing resources by issuing textual commands rather than using graphical interfaces, providing interactive access to an operating system shell, remote control over cloud resources via secure communication protocols, execution of administrative,

[3] National Institute of Meteorology (2025)
[4] National Institute for Space Research (2025)

analytical, and automation tasks, and low-latency, scriptable interaction with distributed systems.

- *Dashboards* [10] providing visual information interface that aggregates, processes, and presents key data, metrics, and indicators in a concise, interactive, and real-time (or near real-time) format to support monitoring, analysis, and decision-making. In this case, provides visualization of water quality indicators (e.g., turbidity, pH, conductivity), tracks hydrological variables (e.g., water level, rainfall, flow), displays spatial information through GIS-enabled maps, monitors sensor health and data availability, and supports a DSS by synthesizing complex datasets into actionable insights.
- *Internet access* [11] available to registered users by means of using any appropriate device (e.g., mobile phones, tablets or computers).

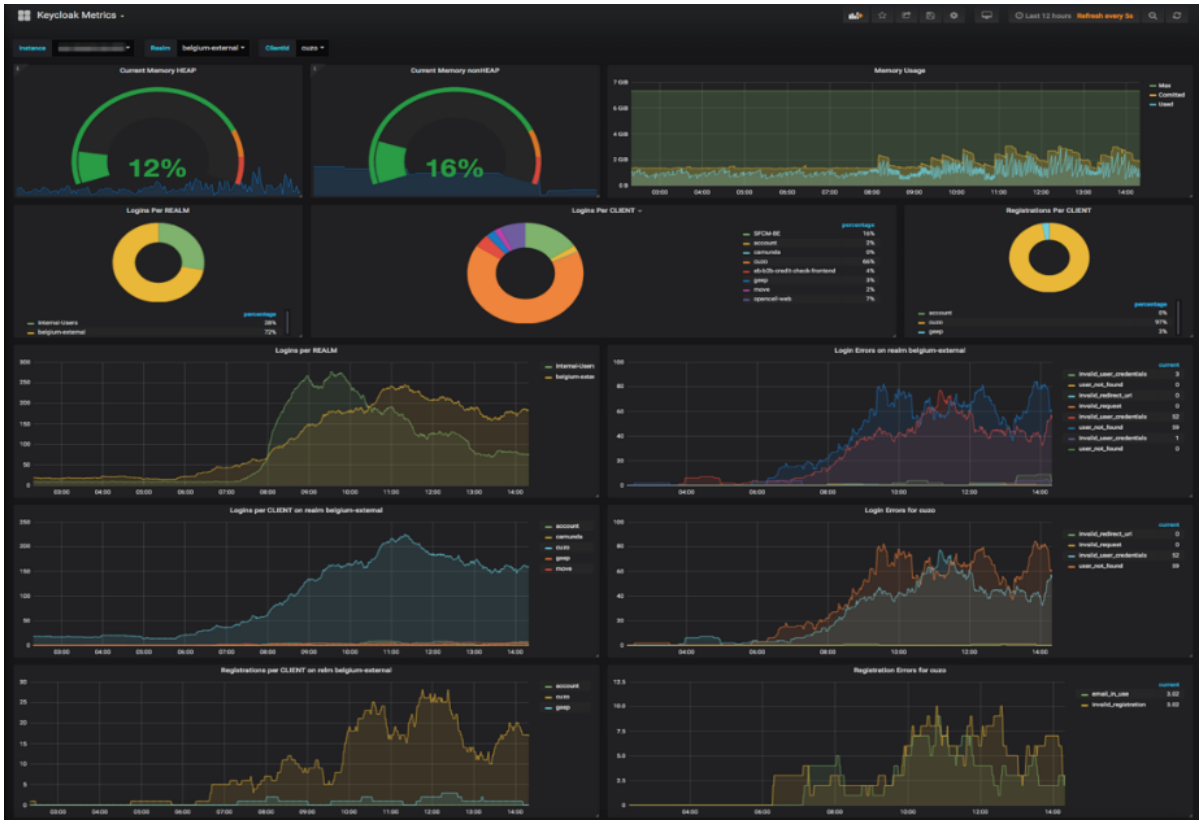
Figure 9: High level theoretical architecture



Source: author, 2026

There are several open-source software systems available that could be used to create dashboards for displaying real-time and historical data – the selection should be made regarding the chosen cloud provider (Figure 10).

Figure 10: Example of a dashboard using Grafana



Source: Grafana Labs (2025)

As illustrated in Figure 10, the use of open-source visualization platforms like Grafana allows for the synthesis of multi-source data into a single operational view. Such a dashboard enables decision-makers to monitor real-time hydrological variations and pollution spikes simultaneously, facilitating immediate interventions that static reports could not support.

The combination of a dashboard tool with a foundation for data analysis such as cloud computing infrastructure would provide a consistent solution for a modern DSS, ensuring the scalability required to meet upcoming needs.

4.3 Engineering the Outcomes

4.3.1 Water Quality Index

The Water Quality Index (WQX) functions as a multidimensional analytical framework that synthesizes extensive physical, chemical, and biological datasets into a single, interpretable

metric. As detailed in Table 11, the most widely adopted indices integrate diverse parameters to provide a comprehensive assessment of aquatic health, effectively bridging the gap between raw laboratory metrics and strategic water resource management.

Table 11: Common WQIs in use

Indicator	Target
Physical	Ph (acidity/alkalinity) Temperature Turbidity Total Suspended Solids (TSS) Total Dissolved Solids (TDS) Electrical Conductivity Secchi Disk Depth/Visibility
Chemical	Dissolved Oxygen (DO) Biochemical Oxygen Demand (BOD) Chemical Oxygen Demand (COD) Nitrate (NO_3^-) Phosphate (PO_4^{3-}) Ammonia (NH_3) Chloride (Cl^-) Sulfate (SO_4^{2-}) Total Phosphorus Total Nitrogen Oxidation-Reduction Potential (ORP) Heavy Metals (Pb, Hg, Cd, etc.)
Biological	Total Coliforms Escherichia coli (E. coli) Cryptosporidium and Giardia Chlorophyll-a (proxy for phytoplankton biomass and eutrophication) Colored Dissolved Organic Matter (CDOM)

Source: author, 2026

These indicators, when combined into indices such as the Water Quality Index (WQX), provide an effective snapshot of river health. For the calculation of WQX, four steps can be performed, described as follows.

1. Selection of Parameters

   A set of physical, chemical, and biological parameters is chosen according to regulatory frameworks and monitoring objectives.

   Commonly included: pH, DO, BOD, Chemical Oxygen Demand, Nitrates, Phosphates, Turbidity, Total Coliforms, Temperature, and Conductivity.

In Brazil, WQI calibration follows CONAMA Resolution 357/2005, selecting nine parameters: DO, fecal coliforms, pH, BOD, temperature, total nitrogen, total phosphorus, turbidity, and total solids (National Council for the Environment, 2026).

2. Transformation into Sub-Indices

   Each parameter is converted into a dimensionless sub-index (q_i) using rating curves or mathematical functions that map raw measurements into a standardized 0–100 scale.

   Example: A DO of 8 mg/L may correspond to qi ≈ 90, while 2 mg/L might correspond to qi ≈ 20.

   These curves reflect ecological thresholds and drinking water standards (e.g., WHO, EPA, ANA/CONAMA in Brazil).

3. Weight Assignment (w_i)

   Each parameter is given a weight to represent its relative importance in water quality assessment.

   Oxygen-related parameters (DO, BOD) usually have higher weights.

   Microbiological contamination (coliforms) also receives high importance due to health risks.

   Nutrients (N, P) and turbidity receive moderate weights.

4. Aggregation Formula

   The most common aggregation is a weighted geometric mean[5]:

$$WQX = \prod_{i=1}^{n} (q_i)^{w_i}$$

   Where:

   - q_i = sub-index of parameter i

[5] The geometric mean is generally preferred over the arithmetic mean when calculating a WQX because it better reflects the way water quality parameters interact and prevents excellent values for some parameters from masking poor values in others, producing a more conservative and environmentally meaningful assessment.

- w_i = weight of parameter i (normalized so that $\sum w_i = 1$)
- Water is then classified into qualitative classes.

To ensure a high-fidelity diagnostic of the river state, the selected monitoring parameters are categorized based on their specific contribution to the equilibrium of the ecosystem. This classification allows for a modular analysis of environmental health, distinguishing between immediate physical changes, long-term chemical alterations, and the biological integrity of the water body. While the core indicators are based on the parameters previously discussed (Table 11), the following table (Table 12) summarizes the resulting qualitative classes used to interpret the final index scores.

Table 12: Water Quality Index

WQX Score	Water Quality Class	Meaning
79–100	Excellent	Suitable for all uses, minimal pollution
51–79	Good	Minor deviations, generally acceptable
36–51	Medium	Some pollution, restricted use for sensitive organisms
19–36	Poor	Polluted, requires treatment for most uses
0–19	Very Poor	Unsuitable for most uses, heavy pollution

Source: CETESB, (2022)

Table 13 presents an overview of how MPC pollution interacts with, or is associated with conventional water quality indicators, based on findings reported in the literature.

Table 13: Link with microplastic detection

Indicator/Method	Pollution Monitoring	Ecosystem Health	Human Consumption	Microplastic Link
pH	Detects industrial/agricultural discharges	Affects bioavailability of toxins	Water taste, corrosion	Influences plastic degradation/release of additives
Dissolved Oxygen (DO)	Organic/chemical pollution	Key for fish survival	Taste/odor proxy	Microplastics reduce DO indirectly (biofilm growth, eutrophication)
BOD / COD	Organic pollution (wastewater, effluents)	Oxygen depletion impacts species	Indirect relevance	Microplastics often co-transport organic pollutants
Turbidity / TSS	Suspended solids (erosion, effluents, plastics)	Reduces photosynthesis	Treatment challenges	Microplastics increase turbidity, tracked via TSS proxies
TDS / Conductivity	Industrial discharges, salinity	Alters aquatic osmoregulation	Taste, suitability	Microplastics often transport ionic pollutants, affecting conductivity
Nitrate / Total Nitrogen	Fertilizer/sewage	Algal blooms, oxygen depletion	Human health risk (methemoglobinemia)	Nutrient-rich waters facilitate plastic–algae interactions
Phosphate / Total P	Detergents, fertilizers	Eutrophication, algal blooms	Treatment challenges	Nutrient hotspots correlate with plastic aggregation
Ammonia	Sewage runoff	Toxic to aquatic life	Strong contamination marker	Co-occurs with microplastics near wastewater outfalls
Heavy Metals (Pb, Hg, Cd)	Industrial pollution	Bioaccumulation	Highly toxic	Plastics adsorb metals, acting as pollutant vectors
Temperature	Thermal discharges	Controls species metabolism	Taste/disinfection by-products	Affects plastic degradation and leaching of additives
Chlorophyll-a	Nutrient loading proxy	Measures algal biomass	Taste/odor issues	Microplastics stimulate algal colonization (biofilms)
Coliforms / E. coli	Sewage contamination	Indirect ecological harm	Drinking water safety	Microplastics act as carriers (“plastisphere” for pathogens)

Indicator/Method	Pollution Monitoring	Ecosystem Health	Human Consumption	Microplastic Link
Cryptosporidium & Giardia	Sewage/agriculture	Wildlife exposure	Human health risk	Microplastics may shelter protozoa from treatment
CDOM	Organic matter inputs	Light penetration, primary productivity	Disinfection by-products	Spectral interference in optical microplastic detection

Source: author, 2026

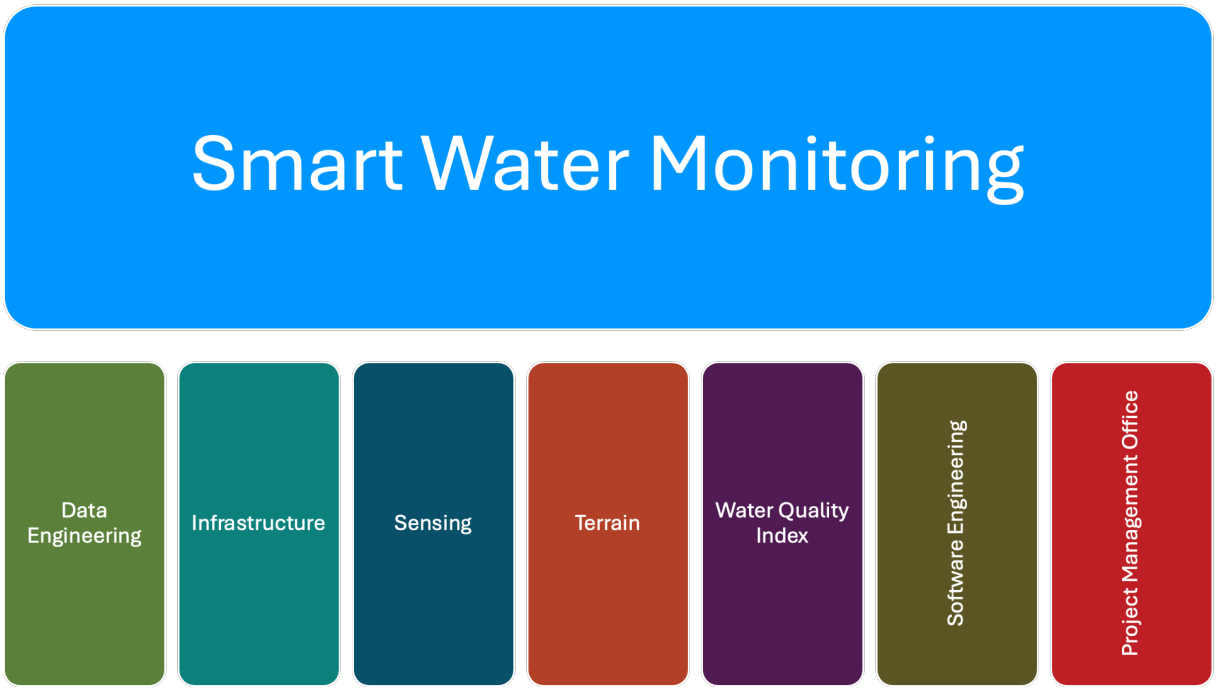
As shown in Table 13, there is a consistent relationship between the presence of MPCs and variations in key water quality indicators, including pH, dissolved oxygen, turbidity, and heavy metal concentrations. These findings suggest that MPC may significantly affect overall water quality, reinforcing the need for targeted research to identify the primary causes and sources of contamination.

4.3.2 Approach to Implementation

In this section it is suggested an approach to allow implementing an initiative capable of delivering what is proposed in this work. Such approach, in the form of a project, presents an organization which will cover necessary steps to establish the required governance for a complex endeavor. It is comprised by 7 areas (see Figure 11), each one of them responsible for: Data Engineering, Infrastructure, Sensing, Terrain, Water Quality Index, Software Engineering, and Project Management Office.

Right after the implementation, this organization will set the foundation for a long term and successful management of this monitoring system.

Figure 11: Areas responsible for the implementation



Source: author, 2026

It is not in the scope of this work to detail each task to implement and deploy such system, nevertheless in the following section it is presented an overall description of each area.

4.3.2.1 Data Engineering

Data engineering focus on designing, building, and maintaining systems that collect, process, store, and make data available for analysis. It involves developing data pipelines, integrating heterogeneous sources, ensuring data quality, and implementing scalable storage

architectures such as data lakes and databases, enabling reliable data flow for analytics, machine learning, and decision-support systems, particularly in complex environments such as environmental monitoring, where large volumes of structured and unstructured data must be efficiently processed and standardized – particularly:

- *Data Ingestion and Integration.* Data engineers design and implement pipelines that ingest heterogeneous data sources into centralized storage systems. These pipelines ensure reliability, schema consistency, and metadata tracking.
- *Data Cleaning, Harmonization, and Quality Control.* Environmental datasets often contain missing values, noise, temporal discontinuities, and inconsistent formats. Data engineers apply preprocessing, outlier detection, timestamp normalization, unit standardization, and sensor-fault filtering before the data feeds modeling pipelines.
- *Data Storage Architecture and Optimization.* Building scalable and cost-efficient storage (data lakes, time-series databases, geospatial repositories) is a core responsibility. This includes defining partition strategies, compression policies, retention periods, and optimizing spatial/temporal queries.
- *Pipeline Orchestration and Automation.* Data engineers schedule and orchestrate ETL/ELT pipelines using workflow managers, building fault-tolerant, self-healing dataflows that ensure continuous ingestion from sensors and satellites.
- *Data Model Design and Standardization.* Designing schemas for time-series data, geospatial layers, WQI datasets, hydrological indicators, MPC detection records, and remote-sensing outputs, defining ontologies and naming conventions.
- *Geospatial Data Engineering.* For river basins, data engineers process geospatial layers using GIS pipelines. Tasks include reprojection, tiling, rasterization, geospatial indexing, and linking environmental variables to coordinates.
- *API Development and Data Access Services.* Data engineering teams build APIs and data-access layers that make curated datasets available to modelers, applications, and dashboards (e.g., Grafana).
- *Ensuring Data Reliability, Security, and Governance.* This includes versioning, audit trails, encryption, access control, backup policies, and compliance with regulatory frameworks.

- *Enabling Machine Learning and Analytics.* Data engineers prepare feature stores, ML-ready datasets, and large-scale training pipelines for forecasting models (e.g., turbidity, TSS, flood risk, MPC proxies).
- *Operational Monitoring and Observability.* Building monitoring dashboards for pipeline health, data latency, data drift, missing records, and sensor failures ensures stable system operations.

4.3.2.2 Infrastructure

Infrastructure is responsible to manage and provision computing resources to support data pipelines and analytics, designing secure network architectures connecting sensors, cloud, and users, while optimizing storage systems for large-scale environmental data. It is designed to ensures reliability, fault tolerance, and high availability through load balancing and recovery mechanisms, implement cybersecurity, automate deployments, and monitor system performance – particularly:

- *Provisioning and Managing Computing Resources.* Infrastructure teams allocate and maintain servers, virtual machines, containers, and cloud services required by data pipelines, databases, dashboards, and ML workflows. They ensure high availability, elasticity, and capacity to support real-time ingestion and analytical workloads.
- *Network Architecture and Communication Management.* They design and maintain network connectivity between sensors, gateways, cloud environments, and user interfaces. Tasks include configuring VPNs, firewalls, routing policies, maintaining secure IoT/WSN communication paths, ensuring redundancy for mission-critical data flows (e.g., flood monitoring).
- *Storage Infrastructure Deployment and Optimization.* This includes installing and maintaining storage systems such as object storage (data lakes), block storage for databases, distributed file systems, time-series storage for sensor streams. They also manage replication, backup, retrieval speed, and cost optimization.
- *System Reliability, Fault Tolerance, and High Availability.* The team builds resilient infrastructures capable of withstanding failures. This includes load balancing, failover clusters, health checks, automated service recovery.

- *Security, Access Control, and Compliance.* Infrastructure ensures cybersecurity at the hardware, OS, and network layers: identity and access management, encryption at rest and in transit, intrusion detection, patching, compliance with standards for environmental data.
- *Deployment, Automation, and CI/CD Pipelines.* The infrastructure team supports DevOps practices by maintaining deployment pipelines, automating rollouts for dashboards, APIs, ML services, and ingestion components, ensuring reproducible environments via containerization.
- *Monitoring and Observability of Infrastructure.* They operate monitoring systems (e.g., Grafana, Prometheus, CloudWatch) to track: CPU/RAM/disk usage, network traffic, sensor connectivity uptime, message-queue throughput, database performance.
- *Managing Edge Infrastructure (Gateways, On-Site Hardware).* For environmental monitoring, infrastructure must support edge devices: local gateways for IoT, edge processors for UAV missions, telecommunication modules (GSM, LoRa, satellite). Tasks include hardware installation, power management (solar), and ruggedization.
- *Geospatial and Remote Sensing Infrastructure Support.* This team prepares infrastructure to handle geospatial workloads: GPU-enabled processing for remote sensing (RS) image classification, tiling servers, high-performance storage for large raster datasets.
- *Disaster Recovery and Continuity Planning.* They develop and test Disaster Recovery plans to guarantee that critical environmental data and early-warning services remain accessible during outages or natural disasters (e.g., floods, storms).

4.3.2.3 Sensing

Sensing is responsible to select appropriate technologies for monitoring water indicators and define sensor specifications by planning strategic placement considering hydrology, pollution sources, and connectivity, followed by installation, calibration, and commissioning – particularly:

- *Sensor Requirements Analysis and Technology Selection.* The sensing team evaluates which sensing technologies are appropriate for each indicator. Tasks include mapping

WQIs to sensor types, defining accuracy, range, detection limits, response time, selecting sensors for flood monitoring.

- *Sensor Placement Strategy and Field Deployment Planning.* Sensing teams determine where sensors should be installed to ensure representativeness and event detection sensitivity. Key tasks: selecting deployment points considering hydrology, topography, pollution sources, flood-prone regions, planning and mounting structures, ensuring safe access and maintenance feasibility, mapping telecommunications availability.
- *Installation, Calibration, and Commissioning of Sensors.* This includes configuring devices and ensuring measurement precision. Key tasks: physical mounting and waterproofing, initial calibration against laboratory standards, configuration of sampling intervals and power modes, verification of telemetry transmission and data integrity.
- *Operation, Maintenance, and Field Servicing.* Continuous operation requires structured maintenance routines. Key tasks: sensor cleaning, anti-fouling measures, periodic recalibration, replacing optical caps, membranes, batteries, desiccants, inspecting solar panels, cables, seals.
- *UAV-Based Sensing and Sampling.* For remote or inaccessible areas, UAV teams perform airborne sensing missions.
- *Satellite Remote Sensing Acquisition and Pre-processing.* Tasks include obtaining and preparing satellite data from platforms. Activities: searching, downloading, and cataloging RS scenes, atmospheric correction and cloud masking, extracting water-body masks and indices, converting reflectance data to geophysical parameters.
- *MPC Sensing and Detection Activities.* Microplastic detection is a specialized sensing domain that may require hybrid approaches. Key tasks: operating optical, microfluidic, and spectroscopic detection devices, collecting and filtering water samples for lab-based MPC quantification, using airborne hyperspectral imagery to detect floating macroplastics, using satellite-derived proxies, integrating AI-based image recognition for MPC particle identification.
- *Telemetry Configuration and Sensor Communication Management.* Sensing teams configure communication between field sensors and cloud platforms, managing

message formats optimizing power consumption for transmission cycles, validating data continuity and signal stability.

- *Data Quality Assurance at the Acquisition Layer.* Before data reaches data engineering pipelines, the sensing team ensures measurement integrity. Tasks: sensor drift detection, flagging anomalous readings, maintaining metadata (sensor model, calibration dates, environmental conditions), validating timestamps and geolocation accuracy.
- *Environmental, Safety, and Compliance Procedures.* Field sensing operations must comply with environmental, safety, and regulatory conditions. Tasks: securing permits for river installations and UAV flights, implementing field safety protocols, ensuring devices meet environmental standards (IP ratings, EMI compliance).

4.3.2.4 Terrain

Terrain is responsible to conduct field surveys to assess site feasibility, including hydrology, access, and connectivity. Key tasks: installing and securing sensors, performing calibration and validation, and ensuring continuous operation through maintenance and troubleshooting. During flood events, Terrain should deploy emergency monitoring and verify conditions. It also manages telecommunications and power systems, ensuring safety and regulatory compliance, and maintaining detailed documentation for traceability and system improvement – particularly:

- *Field Survey and Site Reconnaissance.* Before any installation or sampling, terrain teams perform on-site studies to determine operational viability. Typical activities: assessing river access, stream depth, flow conditions, and bank stability, mapping pollution hotspots, industrial discharge zones, and flood-prone areas, verifying safe access routes, maintenance frequency, and environmental constraints, checking availability of cellular or satellite connectivity.
- *Installation of Sensors and Field Equipment.* Terrain staff install and secure hardware in real environments. Tasks include mounting ultrasonic, optical, or multiparameter probes on bridges, poles, or floating structures, securing data loggers, solar panels, and communication modules, installing rain gauges, water-level sensors, and flow meters, ensuring structural stability during floods or strong flows.

- *On-Site Calibration and Validation.* Field calibration is essential to ensure trustworthy measurements.
- *Routine Maintenance and Troubleshooting.* Terrain teams ensure sensors remain operational under challenging riverine conditions.
- *Field Sampling for Water Quality and Microplastic Analysis.* When automatic sensors are insufficient or require verification, field sampling is executed.
- *UAV Operation in Field Conditions.* Terrain teams support or execute UAV missions for monitoring. Tasks: preparing and launching UAV flights following safety and regulatory guidelines, capturing multispectral/hyperspectral data over rivers, reservoirs, or wetlands, operating drone-based automatic water sampling systems, coordinating UAV flights to validate satellite data or detect floating debris.
- *Flood Event Monitoring and Emergency Deployment.* Terrain operations often include rapid response during hydrological extremes. Tasks: deploying temporary water-level sensors during high-risk periods, conducting manual observations during floods to validate model outputs, verifying bank overflow thresholds, damage, and flow obstructions, applying safety protocols for extreme weather work.
- *Telecommunication and Power Checks.* Terrain personnel ensure communication and energy systems function continuously.
- *Safety, Environmental Compliance, and Legal Procedures.* Terrain teams must comply with regulations governing fieldwork. Tasks: securing permits for river access and UAV flights, following safety protocols for working near water, electrical systems, and during storms, ensuring minimal environmental disturbance.
- *Documentation and Field Reporting.* Accurate documentation ensures traceability and scientific rigor. Tasks: logging maintenance, calibration, and incident reports, recording environmental conditions and anomalies, documenting sampling, reporting deployment feasibility and terrain constraints to engineering and sensing teams.

4.3.2.5 Water Quality Index

The WQX team defines and selects key physical, chemical, and biological indicators aligned with regulations and sensor capabilities, designing normalization and weighting

methods, validate data from sensors, laboratories, and satellites, and compute the index over time. The team ensures quality control, regulatory compliance, and documentation, and translates results into dashboards and decision-support tools for effective water management and early-warning systems – particularly:

- *Definition and Selection of Water Quality Indicators.* The WQX team identifies which physical, chemical, and biological parameters will compose the index, ensuring compatibility with sensor availability and laboratory procedures.
- *Parameter Weighting and Normalization Design.* The team defines mathematical methods for transforming raw values into standardized sub-indices.
- *Acquisition and Validation of Input Data.* The WQX team ensures that all required parameters are collected accurately. Tasks: validating sensor measurements, acquiring laboratory results for nutrients, bacteria, metals, and organics, confirming consistency with satellite-derived proxies, ensuring temporal alignment and metadata quality.
- *Computation of the Water Quality Index.* The core analytical task: converting multi-parameter data into a single index. Tasks: applying WQX formula, handling missing data, outliers, and non-detect values, generating time series (hourly, daily, monthly), integrating automated computation into cloud pipelines.
- *Spatial Analysis and Mapping of WQX Across Basin.* The team generates geospatial outputs for situational awareness.
- *Trend Analysis, Classification, and Threshold Evaluation.* WQX team classify water bodies and monitor trends.
- *Integration with Remote Sensing for WQI Estimation.* Some parameters can be derived or supplemented by satellite imagery. Tasks: deriving turbidity, TSS, chlorophyll-a from Sentinel-2, Landsat, MODIS, validating RS-derived parameters using *in-situ* measurements, incorporating satellite data in WQX computation where feasible.
- *Microplastic Indicators Integration.* Emerging research considers microplastics as a component of water quality. Tasks: evaluating MPC concentration as a supplementary indicator, integrating microfluidic, optical, and AI-based MPC data into WQI frameworks, using SSC to infer probable microplastic loads.

- *Quality Assurance, Documentation, and Regulatory Compliance.* WQI results must meet institutional and scientific standards. Tasks: documenting methods, formulas, calibration standards, maintaining audit trails, ensuring compliance with environmental regulations, producing periodic WQI reports for agencies, policymakers, and the public.
- *Communication and Decision-Support Integration.* The WQX team transforms analytical results into actionable insights.

4.3.2.6 Software Engineering

Software Engineering teams design, develop, test, and maintain applications that support data collection, processing, and visualization. Tasks include building user interfaces, developing APIs and backend services, integrating data pipelines, implementing algorithms and ML models, and ensuring system scalability and performance. They also manage version control, testing (unit/integration), debugging, and deployment using CI/CD practices – particularly:

- *Requirements Engineering and Systems Specification.* Software engineers translate domain needs into precise technical requirements for applications and services. Tasks include defining functional and non-functional requirements (latency, robustness, scalability for IoT data), capturing user needs for dashboards, APIs, and decision-support features, modeling system behavior (use cases, data flows, architectural diagrams).
- *Application and Platform Development.* Software engineering teams build the software components that enable data collection, processing, visualization, and analytics. Tasks: developing data ingestion services for IoT, UAV, and satellite data, designing backend services (REST APIs, microservices, message brokers), implementing user interfaces such as dashboards and control panels, building modules for WQI computation and flood-alert logic.
- *Real-Time Processing and Stream Management.* Environmental systems generate continuous, high-velocity streams. Tasks: implementing real-time data pipelines, managing event-driven architectures and streaming analytics, processing sensor events for anomaly detection, flood thresholds, or WQI triggers.

- *Integration with Machine Learning and Analytical Models.* Software engineers operationalize machine learning models for hydrology, water quality, and microplastic detection. Tasks: creating model endpoints and inference services, integrating ML pipelines with cloud storage and streaming inputs, implementing hybrid systems, enabling LSTM or hybrid models for water-quality forecasting.
- *Database and Data Layer Development.* Although data engineering manages infrastructure and processing, software engineering implements the logical data access layer.
- *Interface Development for Dashboards and DSS Tools.* Water monitoring projects rely heavily on visualization and decision-support interfaces. Tasks: building visualization panels, implementing geospatial layers, charts, WQI maps, turbidity or SSC heatmaps, designing alert interfaces for pollution or flood detection, providing user-friendly access to historical and real-time data.
- *Communication Protocols and IoT Integration.* Software engineering ensures that device-level data enters the system seamlessly.
- *Cybersecurity Engineering.* Software teams ensure secure access and safe system operation. Tasks: implementing authentication, authorization, secure APIs, encrypting data in transit and at rest, preventing sensor spoofing, tampering, or injection attacks, logging and auditing for compliance.
- *DevOps, CI/CD, and Automated Deployment*[6]. Software engineers implement automation for building, testing, and deploying services. Tasks: setting continuous integration pipelines for code quality, enabling automated deployments to cloud infrastructure, implementing blue-green or canary models for high-availability updates, containerizing applications.
- *Testing, Validation, and Quality Assurance.* The team ensures that software is reliable and correct. Tasks: unit, integration, system, and performance testing, simulation of

[6] DevOps is a collaborative approach integrating software development and IT operations to automate workflows, improve deployment frequency, and enhance system reliability through continuous integration and continuous delivery (CI/CD) practices, whereas CI/CD (Continuous Integration and Continuous Delivery/Deployment) is a DevOps practice that automates code integration, testing, and release processes, enabling frequent, reliable software updates through automated pipelines and reducing deployment risk.

sensor failure, communication loss, or flood spikes, cross-validating numerical outputs, verifying interoperability with sensing, infrastructure, and data engineering layers.

- *Documentation and User Support.* A core function of software engineering is making systems understandable and maintainable. Tasks: writing API documentation, user guides, and developer manuals, maintaining version control and release notes, supporting stakeholders.

4.3.2.7 Project Management Office

The Project Management Office (PMO) is responsible for defining, maintaining, and ensuring project management standards, governance, and best practices across an organization. Its core purpose is to increase project success rates, optimize resources, and ensure project alignment with strategic business objectives – particularly:

- *Project Planning, Structuring, and Methodological Governance.* The PMO defines the organizational structure for the project, timeline, methodology, and milestones. Tasks: establishing scope, deliverables, and success criteria, defining research phases, field deployment cycles, etc.
- *Cross-Team Coordination (Sensing, Data Engineering, Infrastructure, Software, Terrain).* The PMO ensures smooth coordination among multidisciplinary teams.
- *Risk Management and Contingency Planning.* The PMO identifies, monitors, and mitigates risks across the full project lifecycle.
- *Budgeting, Resource Allocation, and Procurement Oversight.* The PMO manages resources across sensing, cloud, UAV, and analytical components.
- *Timeline, Deliverables, and Milestone Tracking.* The PMO monitors progress and ensures timely execution.
- *Stakeholder Management and Institutional Coordination.* The PMO manages communication and alignment with all identified stakeholders.
- *Documentation, Compliance, and Reporting.* The PMO ensures structured, auditable documentation.

- *Quality Assurance and Standardization.* The PMO enforces standards across all teams. Examples: standard operating procedures for sensor calibration, sampling, UAV missions, consistent data quality rules for WQIs, remote sensing (RS) parameters, and microplastic analysis, coding standards for software and data pipelines, periodic audits and validation checks.
- *Strategic Alignment and Benefit Realization.* The PMO ensures the project remains aligned with its strategic purpose: providing actionable DSS capabilities, improving PCJ basin monitoring, enabling early-warning systems (pollution, floods, microplastics), supporting public policy development.
- *Communication, Knowledge Transfer, and Capacity Building.* The PMO maintains knowledge continuity and develops internal/partner capabilities. Tasks: organizing workshops on sensors, RS, cloud workflows, and WQI interpretation, transferring methodologies to local agencies, enabling long-term operation beyond the implementation phase.

5 CONCLUSIONS

This work is a theoretical and methodological proposal. Its main contribution lies in investigating available technologies, assessing feasibility for the PCJ region, and proposing a reference architecture for future adoption by the PCJ Agency.

PCJ Basins resides in a highly populated area with a concentration of all types of industries, therefore defining which spots are most appropriate to install sensors depends upon a deep understanding of geography, topography, rain distribution, flood prone areas, potentially polluting industries, and telecommunication coverage. Specifics related to sensors such as technology, installing idiosyncrasies, and price must not be overlooked.

There is clearly a pressing need for a comprehensive and integrated water monitoring system for the PCJ river basins. Rapid urbanization, industrialization, and climate change have exacerbated water scarcity and pollution in this region. Current monitoring efforts by the PCJ Agency are robust in measuring flow and reservoir levels but fall short in providing detailed WQIs and flood forecasting.

Combinations of technologies are pivotal for transforming water monitoring. From the standing point of proposed architecture, opportunities may include real-time monitoring through IoT, scalability and flexibility provided by modularity as construction philosophy. On the other hand, as limitation, data transmission is a challenge: sensors have energy constraints (particularly in remote off-grid regions, battery replacement may be a difficult task), compatibility among models, connection availability, and eventually high setup costs (Iancu; Ciolofan; Drăgoicea, 2024; López-Ramirez; Aragon-Zavala, 2023).

It is important to mention that MPC detection has evolved significantly, with technologies ranging from spectroscopy performed in laboratories to emerging portable and field-deployable solutions, such as advances in portable optical systems that would enable real-time detection in riverine and coastal environments, reducing the dependence on laboratory analysis (Chabot; Marteinson, 2024).

There are significant advances in analysis of remote sensing, drone-based imaging, and the emerging but still experimental potential of satellite observations for large-scale MPC monitoring. Airborne detection shows promise in coastal and estuarine zones, whereas satellite detection remains mostly theoretical due to spatial resolution constraints and interference from dissolved organic matter or suspended sediments. There are important challenges associated

with MPC detection in complex environments and the necessity for automation, miniaturization, and integration of machine learning for image or spectral analysis along with that.

According to Mukonza; Chiang (2022) some key challenges are: lack of standardized methodologies for sampling, identification, and quantification across different environments; detection limits for small-sized microplastics (particularly <50 μm) remain problematic in field-based systems; high background noise from natural particulates (e.g., sediments, organic matter) in optical or remote sensing systems; scalability issues, particularly for satellite and drone detection, due to resolution constraints.

The future of microplastic detection will depend on combining multiple technologies: portable sensors for local real-time detection, drone-based surveys for regional assessments, and ongoing research toward viable satellite-based observation. Such integration will support the development of early-warning systems and pollution mitigation strategies in riverine and marine environments.

UAVs are good choices when accessing areas that are hard to reach (when equipped with advanced sensors and/or cameras, detailed water quality metrics can be captured). Also, when compared to satellite data they may offer a more economical solution or smaller-scale studies or specific regions. They may be particularly useful in emergencies (such as pollution or flooding events, ensuring timely data collection), and as well as validating satellite data (Dube et al. 2023).

Implementing, deploying and operating the proposed architecture will require specialized personnel. Orchestrating such endeavor presents a challenge that will span from selecting the cloud provider, sensor technology, integration of many devices, data sources, and presenting methods, for example: non-contact sensors (e.g., radar level) are preferred in flood zones due to low maintenance and safety; telemetry is critical for early warning and should be integrated with hydrological models and DSS tools; redundancy (e.g., combine level, rainfall and velocity for robust flood forecasting); and calibration (regular verification against manual measurements ensures sensor accuracy). In addition, a project of this magnitude entails financial costs that must not be overlooked; however, it offers a replication opportunity to other river basin agencies.

In summary this work proposes to: a) implement an integrated monitoring architecture (deploy a hybrid system combining locally placed IoT sensors, UAVs, and satellite data streams into a cloud-based DSS with user-friendly dashboards for real-time monitoring and historical analysis); b) strategize sensor deployment (prioritize sensor placement at critical points such as river confluences, pollution hotspots, and flood-prone areas; use cellular or satellite communication depending on coverage availability); c) expand WQIs monitoring (incorporate sensors for chemical, physical, and biological indicators to capture a comprehensive water quality profile); d) adopt MPC detection innovations (integrate emerging microfluidic, optical, and AI-driven detection systems for *in-situ* monitoring, while using satellite proxies to enhance spatial coverage); e) apply data integration and AI (utilize ML models for flood prediction, water quality forecasting, and anomaly detection by integrating current data with historical datasets from the PCJ Agency); f) engage stakeholders and build capacity (involve stakeholders such as local governments, civil defense, academia, and communities, and provide training on data interpretation, dashboard usage, and sensor maintenance); g) align policy and funding (seek alignment with national and state policies and secure funding through public-private partnerships to ensure the system's sustainability); and h) implement scalability and replication (design a DSS to be modular and scalable, allowing replication in other Brazilian river basins facing similar challenges).

Future research should prioritize developing standardized methodologies for detecting and quantifying microplastics, particularly particles smaller than 50 μm, using advanced optical and AI-based techniques to overcome interference from natural particulates.

Efforts are also needed to design energy-efficient, autonomous IoT sensor networks powered by renewable sources to enable continuous monitoring in remote riverine regions. Integrating multi-source datasets through hybrid machine-learning models will enhance predictive analytics for water quality and flood forecasting.

Research should further advance scalable, cloud-based decision-support systems that promote interoperability, open-data governance, and replication in other Brazilian river basins.

Additionally, social and institutional studies are required to align stakeholders, policies, and funding mechanisms to ensure long-term system sustainability, considering that such an implementation of a (near) real-time system with easy public access, most certainly will reposition access to information, mainly when related to water availability and quality.

Finally, systematic field campaigns combining ground and remote observations should be conducted to calibrate satellite-derived indicators, improving model accuracy and strengthening confidence in data-driven watershed management.

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