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AquaTrace: A Solar-Powered Autonomous Surface Vehicle for Adaptive Water Purification and Pollution Source Localization

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Abstract: Water pollution, a key global environmental issue, is especially critical in intensely contaminated water bodies such as river stretches, lakes, and estuaries, where continuous water-quality monitoring and remediation are impractical with current existing approaches. This paper presents AquaTrace, a multimodal, autonomous river basin water-quality monitoring, water-source localisation, and remediation platform based on a solar-powered Autonomous Surface Vehicle (ASV). The system proposes a control architecture based on a Raspberry Pi 5 and an ESP32 microcontroller, a six-stage water purification sequence, real-time water-quality measurement instrumentation, and a Pollution Gradient Ascent (PGA) navigation approach to localise pollution sources. A physical prototype is constructed to verify the platform design, including buoyancy, mobility, subsystem integration, and autonomous operation in an aquatic environment. To scale the platform for large-area operations, simulation studies are conducted using literature values for water-quality parameters from polluted water bodies, such as Lake Bellandur and the Ganga and Yamuna River stretches. The feasibility of large-scale water-quality analysis and remediation operations in complex contamination domains has been demonstrated through the simulation platform.

Keywords: Autonomous Surface Vehicle (ASV); Water Purification; Pollution Gradient Ascent (PGA); IoT Water Monitoring; Aquatic Environment; Global Environmental Issue; Autonomous Operation.

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1. Introduction

Water pollution is one of the most serious problems facing our environment in the twenty-first century. Industrialization, urbanization, increased fertilizer use, and inefficient wastewater treatment are degrading lakes, rivers, and other water bodies worldwide. Not only does water pollution destroy aquatic life, but it also poses many threats to human health, agriculture, the economy, and biodiversity. With the expansion of cities and urban areas, researchers are seeing an inevitable increase in water

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quality that must be managed effectively and on a large scale. Traditional water quality measurement methods, which are scheduling-based, relatively costly, labour-intensive, and lack continuous, real-time measurement capabilities, are unable to address this problem [1]; [2]. The situation in India is more alarming, as millions of people depend heavily on river systems such as the Ganga and Yamuna for drinking water, irrigation, transportation, and cultural purposes. Several studies have reported high levels of BOD (Biochemical Oxygen Demand) and COD (Chemical Oxygen Demand), suspended solids, heavy metals, and microbial contaminants across various stretches of these rivers.

The implementation of sizable strategies, such as the Ganga Action Plan (GAP) and Yamuna Action Plan (YAP), has still proved inadequate in achieving the desired standards or acceptable water-quality levels. The ever-changing nature of pollution sources complicates the large-scale monitoring and cleanup of water bodies [1]. An additional case study of major urban water pollution is Bellandur Lake in Bangalore. The lake receives a constant load of untreated sewage and industrial effluents, leading to eutrophication, toxic foam formation, decreased dissolved oxygen, and the accumulation of heavy metals [5]. The manifest episodes of environmental pollution at Bellandur Lake point to the shortcomings of current remediation techniques. It also highlights the imperative need for novel technological systems to monitor pollution and support restoration efforts. Given the availability of published water-quality datasets, Bellandur Lake is an ideal candidate for testing the effectiveness of an advanced water-restoration system in real-world pollution scenarios. To compensate for these shortcomings, this paper offers a solution in the form of AquaTrace, a solar-powered Autonomous Surface Vehicle (ASV) that both adapts to time- varying water quality conditions and locates pollution sources.

The proposed system architecture employs a combination of a Raspberry Pi 5 and an ESP32-based control platform, a six-stage purification system, zero-latency environmental sensing, and a multimodal navigation strategy called Pollution Gradient Ascent (PGA). Unlike traditional monitoring vessels, Aqua-Trace aims to identify high-pollution zones while paving the way for future remediation efforts. Furthermore, secure forensic reporting devices are integrated, employing cryptography to enable future regulatory activities. A physical prototype was assembled to demonstrate the platform's viability in terms of buoyancy, navigation, and subsystem compatibility [3]. To study the system's operation at a large scale, simulations were performed on sets of water-quality data from the literature that varied the characteristics of Bellandur Lake, including pollution levels. The simulations estimated how pollution was localised, purified, and how the system reacted to the given pollution sources. The primary contributions of this work are summarised as follows:

- Design and develop a solar-powered autonomous surface vehicle prototype for water restoration applications.
- A natural-gradient-based approach for browsing solutions based on a Pollution Gradient Ascent (PGA) framework for autonomous source location is proposed.
- Design of a six-stage adaptive water-purification architecture for autonomous future use.
- Development of a simulation framework using literature-based data sets for Bellandur Lake, the Ganga River, and the Yamuna River.
- Unified system for merging environmental monitoring, pollution detection, and forensic-reporting concepts.

2. Related Work

Recently, autonomous, IoT-enabled water-quality monitoring systems have become increasingly popular due to the growing demand for real-time environmental monitoring. Water-quality monitoring has traditionally been performed by manually sampling Water and analysing it in a laboratory, which is often costly and time-consuming and does not provide real-time information. Therefore, many researchers have investigated tracking environmental parameters using embedded systems, wireless communication techniques, and autonomous robotic vehicles [7]; [8]. A few researchers have proposed and implemented IoT-enabled water-quality-monitoring infrastructures, capable of providing real-time measurement of pH, turbidity, dissolved oxygen (DO), temperature, TDS, etc. Singh et al. [6] have presented an IoT-enabled River Ganga real-time monitoring system to show the importance of quantitative real-time environmental data collection. Kumar et al. [7] also proposed an IoT-based framework for remotely monitoring river water quality using a sensor network.

Sugiharto et al. [8] have studied the importance of selected water quality index (WQI) parameters for an intelligent environmental management system [9]. These infrastructures are designed for data collection and monitoring, but not for pollution reduction or remediation. Significant improvements in ASV technology have enabled the integration of mobile sensing platforms capable of capturing environmental data across larger bodies of Water. ASVs may cover larger distances than stationary monitoring stations and can be operated in hazardous or otherwise inaccessible areas. Zhang et al. [13] reported an autonomous water-quality monitoring system that employed uncrewed aquatic vehicles to collect environmental data [13]. Other efforts have combined GPS-based navigation, onboard imaging, and wireless data communication modules to enhance the capabilities of autonomous environmental monitoring systems. In general, these previous efforts are focused on sensing and surveillance, with less emphasis on adaptive remediation strategies. Another significant problem in water bioresource management is identifying pollution sources.

Most current pollution monitoring systems do not provide autonomous identification of pollution sources; instead, they collect pollution data for later analysis. Improvement efforts have focused on several optimization and path-planning methods to enable effective environmental monitoring and hotspot identification [11]. Despite increased efficiency, most existing systems still rely on predetermined navigation paths or require human intervention. Autonomous systems for identifying pollution hotspots on the fly remain desirable. Water purification technologies have advanced significantly as well. Standard treatment methods use sedimentation, activated carbon adsorption, membrane filtration, ion exchange, and ultraviolet (UV) disinfection to remove physical, chemical, and biological pollutants from Water [15]; [16]. These technologies have been successful at both municipal and industrial treatment plants. While these technologies have been implemented, their integration into a mobile autonomous platform has been scarcely studied. Most documented environmental robotic systems have used these technologies solely for monitoring.

Simultaneously, the environmental agencies have been introducing more credible and verifiable environmental evidence to monitor compliance and pursue pollution. Regulatory standards formulated by the CPCB, US EPA, and the EU-WFD under the Water Framework Directives stress water quality monitoring and sustainable environmental responsibility [10]. However, secure forensic reporting methods are rarely integrated into autonomous water-monitoring platforms. Most of the existing systems send sensor readings to cloud platforms but lack cryptographic verification, tamper resistance, and evidence-oriented reporting architectures. Four gaps have been identified based on our survey. Most systems lack remediation abilities and focus solely on water quality monitoring [12]. The second gap is a lack of, or limited, pollution-source localization. Thirdly, forensic-grade environmental reporting had not been applied to unmanned aquatic platforms. Finally, very few integrated solutions exist that combine monitoring, localisation, remediation, and security.

Researchers aim to fill these gaps with AquaTrace, our vision for a cohesive system that enables autonomous navigation, self-adapting water treatment, pollution-source tracking, and tamper-proof environmental reporting within a single solar-powered Autonomous Surface Vehicle (ASV). By design, our framework enables environmental monitoring and directed restoration operations, rather than just passive sampling like most existing systems, presenting a strong [17]. Table 1 illustrates the shortcomings of current water-quality monitoring/remediation platforms. While some works describe monitoring or remediation solutions, comprehensive works that feature autonomy/navigation alongside pollution-source localisation remain relatively few. Additionally, forensic reporting features are scarce among aquatic remote monitoring platforms. AquaTrace aims to fill this void with a complete system that offers monitoring, localisation, adaptive purification, and forensic reporting, all in an autonomous package [18].

Table 1: Comparison of existing water quality monitoring and restoration systems

Study	Mon.	Nav.	Purif.	Local.	For.
Singh et al. [6]	Yes	No	No	No	No
Kumar et al. [7]	Yes	No	No	No	No
Zhang et al. [13]	Yes	Yes	No	Limited	No
Conventional Treatment Systems [15]; [16]	No	No	Yes	No	No
AquaTrace (Proposed)	Yes	Yes	Yes	Yes	Yes

2.1. Abbreviations

- Mon. = Real-Time Monitoring
- Nav. = Autonomous Navigation
- Purif. = Water Purification
- Local. = Pollution Source Localisation
- For. = Secure Forensic Reporting

2.2. System Architecture

The major hardware components of the proposed AquaTrace architecture are summarised in Table 2. These components collectively support sensing, navigation, communication, propulsion, and energy management functions required for autonomous environmental monitoring and future remediation operations. AquaTrace's overall system architecture is layered, comprising perception, control, communication, and actuation subsystems, as shown in Figure 1. This scalable system architecture was designed to enable autonomous environmental monitoring, pollution-source localization, and future adaptive water-restoration operations. An initial physical platform was prototyped and validated for mobility and subsystem integration capabilities. Further purification and forensic functionality were explored through system-level design and modelling.

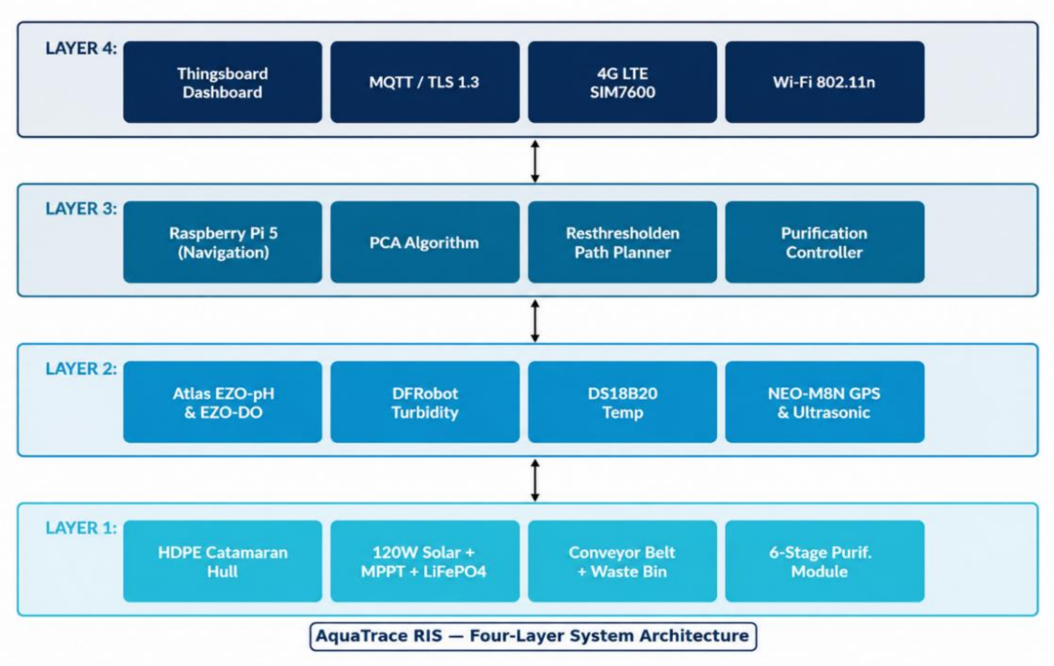

Figure 1: Operational workflow of the proposed pollution gradient ascent (PGA) framework

2.2.1. Perception Layer

The Perception layer provides the environment and navigation awareness that AquaTrace needs. For AquaTrace's full- scale deployment, the Perception layer includes water-quality sensors to measure pH, dissolved oxygen (DO), turbidity, total dissolved solids (TDS), and temperature. A GPS receiver is used to determine real-time position. Finally, an ultrasonic sensor detects obstacles for collision avoidance: building Blocks and Architecture Hardware Components. The control layer is the brain behind AquaTrace. The current architecture uses a Raspberry Pi 5 as a higher-level controller, while an ESP32 microcontroller serves as a lower-level controller, interfacing with sensors and control outputs. On the Raspberry Pi, navigation routines, environment processing, higher-level communication, and other system-level functionality would be implemented. Sensor data would be shared over a serial communication interface between the Raspberry Pi and the ESP32, which would also pass commands to control outputs.

2.2.2. Communication Layer

The communication layer enables remote monitoring of AquaTrace and will serve as the basis for future forensic reporting capabilities. Under the current architecture, sensor measurements, navigation data, and environmental observations can be sent to a ground station via wireless networks. Integration with encryption and cryptographic signing can be used in future work to provide tamper-proof reporting of environmental data.

2.2.3. Actuation Layer

The AquaTrace Actuation layer would allow the system to move and steer through Water. The demonstration platform used a styrofoam boat to demonstrate proof-of-concept mobility. AquaTrace will utilise two brushless DC thrusters to propel and steer itself. With this mobility base, future work includes programming pollution source localisation and dynamically changing cleanup paths.

Table 2: Key hardware components and their functions in the proposed AquaTrace architecture

Component	Purpose
Raspberry Pi 5	High-level processing, navigation, and system coordination
ESP32	Sensor acquisition and actuator control
GPS Module	Position tracking and geolocation
Ultrasonic Sensor	Obstacle detection and collision avoidance
Water Quality Sensors	Environmental monitoring and pollutant assessment

Brushless DC Thrusters	Propulsion and maneuverability
Solar Panel	Renewable energy harvesting
$LiFePO_4$ Battery	Energy storage and power supply

2.2.4. Power Layer

Lastly, the full-scale AquaTrace system includes a solar charging architecture. This includes a rechargeable battery, power management board, and solar charging panels. This allows for less frequent charging of the device and longer monitoring sessions.

2.3. Proposed Adaptive Water Purification Framework

To successfully restore polluted aquatic environments, a combination of treatment processes is needed to remove physical, chemical, and biological contaminants. AquaTrace addresses this requirement through a proposed six-stage adaptive purification framework for future integration in an autonomous surface vehicle platform. The framework combines established water-treatment techniques with sensor-enabled decision-making to enable adaptive remediation across various pollution scenarios. The proposed purification architecture consists of six successive treatment stages, each one for a specific class of contaminants. These stages are designed to work together to reduce suspended solids, organic pollutants, heavy metals, and microbial contamination typical of polluted rivers and urban lakes. Figure 2 shows a schematic diagram of the purification framework.

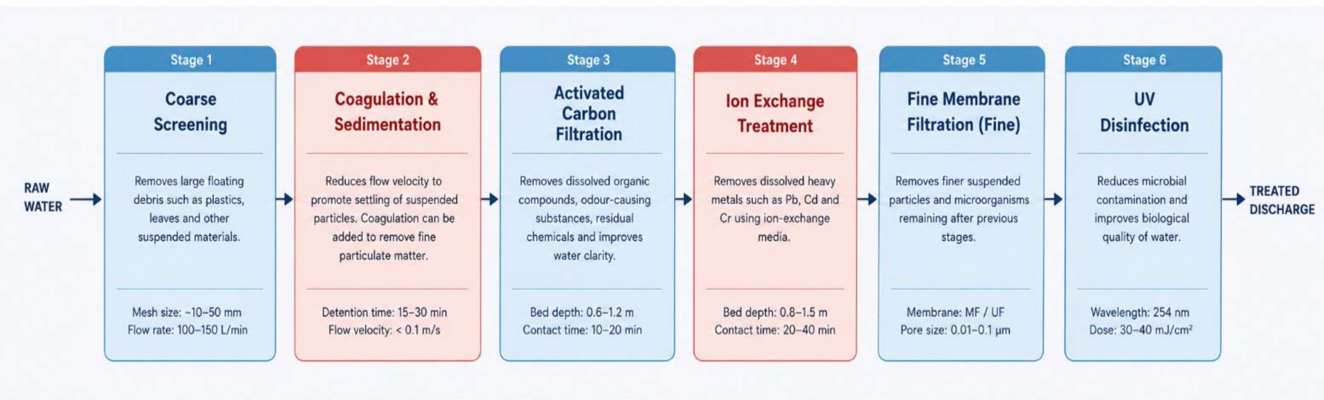

Figure 2: Conceptual six-stage adaptive purification framework proposed for future integration into the AquaTrace platform

Stage 1: Coarse Screening

The first stage implements a coarse screening mechanism intended to trap large floating debris, such as plastics, leaves, and other suspended materials. Removal of these contaminants prevents blockage and enhances the effectiveness of downstream treatment steps.

Stage 2: Coagulation and Sedimentation

After preliminary screening, the Water is passed into a sedimentation chamber, where the flow velocity is reduced to promote the settling of suspended particles. Coagulation processes can be added to improve the removal of fine particulate matter and turbidity.

Stage 3: Activated Carbon Filtration

Activated carbon filtration is proposed to remove dissolved organic compounds, odor-causing substances, residual chemicals, and other contaminants that affect water quality. The purpose of this stage is to improve the Water's chemical properties and overall clarity.

Stage 4: Ion Exchange Treatment

In the fourth stage, ion-exchange media are used for the specific removal of dissolved heavy metals such as lead (Pb), cadmium (Cd), and chromium (Cr), which are often reported in polluted water bodies such as Bellandur Lake and a few parts of the Yamuna River [4]; [14].

Stage 5: Fine Membrane Filtration (Fine)

A membrane filtration step is included to remove finer suspended particles and microorganisms that may be present after the previous treatment stages. Depending on the future deployment needs, microfiltration or ultrafiltration technologies can be used.

Stage 6: UV Disinfection

The final stage is ultraviolet (UV) disinfection to reduce the microbial contamination and improve the biological quality of the Water. UV treatment provides an extra layer of defense against pathogenic microorganisms without the use of chemical disinfectants. The proposed purification framework is designed to be adaptive based on feedback from onboard water-quality sensors. Future implementations may use sensor measurements, such as turbidity, dissolved oxygen, pH, and total dissolved solids, to dynamically adjust treatment priorities and operating conditions. This adaptive approach has the potential to improve energy efficiency while maintaining effective pollutant removal under varying environmental conditions. In the current study, a simulation-based analysis using literature-derived pollution datasets representative of Bellan- dur Lake and selected river environments was performed to evaluate the purification framework. The framework offers a conceptual basis for future validation studies at the laboratory and field scales with physical purification hardware.

2.4. Dual-Mode Operational Framework

AquaTrace uses a dual-mode operational framework to address environmental cleanup and pollution documentation needs, including Remediation Mode and Forensic Mode. These two modes of operation enable the platform to recover. Water quality also enables environmental monitoring and evidence gathering. The framework is designed to transition between states based on environmental conditions and mission objectives.

2.4.1. Mode of Remediation

Remediation Mode is the primary operating mode of the AquaTrace platform. In this mode, the ASV runs through the target water body and collects environmental parameters using onboard sensors. The navigation system uses pollution measurements and location data to spot areas with high contamination levels. In the case of potential pollution hotspots, the vehicle can focus its operations in the area and activate the proposed purification framework. This mode is designed to make the treatment more effective by concentrating efforts on the most polluted areas, rather than spreading resources uniformly across the water body. Remediation Mode may enable flexible treatment strategies for future large-scale deployments where the intensity of purification is adapted to real-time environmental conditions. This adaptability could lead to improved efficiency, reduced energy waste, and more targeted remediation.

2.4.2. Forensic Mode

Forensic Mode is used for environmental monitoring, documentation, and regulatory reporting. Under abnormal environmental conditions, e.g., sudden surges in turbidity, high levels of pollutants, or rapid changes in water quality parameters, the system can prioritise data collection and dissemination. Within this framework, observations of the environment could include sensor readings, geographic coordinates, timestamps, and visual evidence captured by on-board imaging systems. Together, these data points form a structured record of environmental conditions and possible pollution events. Future versions could use cryptographic methods (digital signatures, encrypted communication) to improve data integrity. Such measures can help ensure the authenticity of environmental records and protect them against unauthorized modification during storage and transfer.

2.4.3. Change of Smart Mode

A key feature of the AquaTrace framework is its ability to switch operating modes based on environmental data. Instead of relying solely on manual control, the system continuously evaluates sensor data and selects the most appropriate operational state. Under normal conditions, for example, the vehicle may be performing monitoring and restoration activities when in Remediation Mode.

If the sensors detect a major pollution event, the system can temporarily switch to Forensic Mode to capture the event and collect environmental evidence. After the documentation is completed, the vehicle can return to remediation tasks. This event-driven strategy allows AquaTrace to balance restoration goals with environmental accountability needs. This method is especially important in aquatic environments. Where pollution sources can be intermittent, mobile, or hard to detect through standard monitoring methods (Table 3).

Table 3: Operational modes of the proposed AquaTrace framework

Mode	Primary Objective	Key Functions
Remediation	Pollution Reduction	Water-quality monitoring, pollution localisation, and adaptive purification
Forensic	Environmental Documentation	Data acquisition, geotagging, evidence collection, and reporting

2.4.4. Operational Advantages

This dual-mode framework offers several benefits over traditional water-quality monitoring systems. First, it merges environmental restoration with environmental reporting into a single platform. Second, it allows for targeted responses to new pollution events. Third, it lays the groundwork for future integration of smart decision-making algorithms that can assist with autonomous environmental management. While the current study primarily focuses on design and simulation evaluation, the dual-mode framework provides a flexible foundation for future deployments that include autonomous monitoring, adaptable remediation, and secure environmental reporting. Table 4 summarises the two operational modes of Aqua- Trace and their corresponding objectives and functionalities.

2.5. Pollution Gradient Ascent (PGA) Framework

A key objective of AquaTrace is to identify pollution hotspots within contaminated aquatic environments. To achieve this objective, a Pollution Gradient Ascent (PGA) framework is proposed (Figure 3).

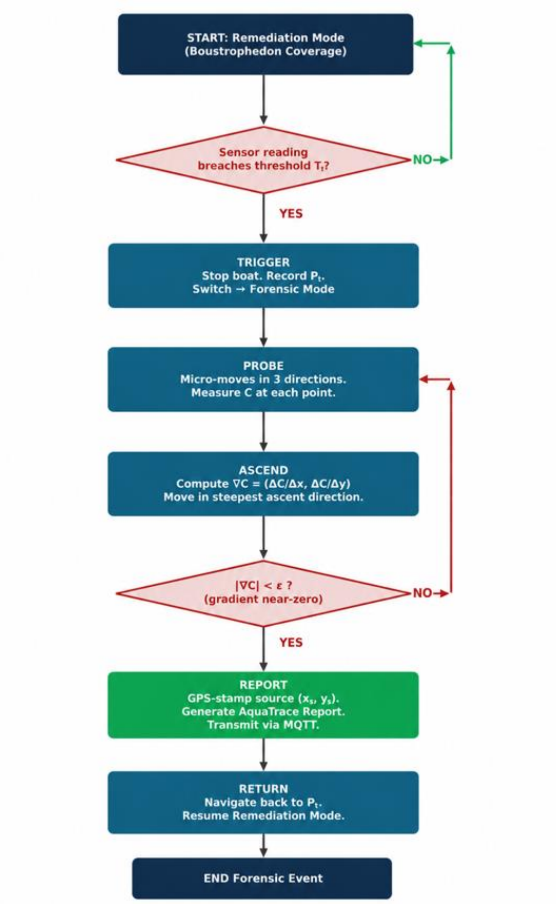

Figure 3: Pollution gradient ascent (PGA) algorithm flowchart

The framework enables the autonomous surface vehicle to estimate local pollutant concentration gradients and autonomously navigate toward regions exhibiting elevated pollution levels.

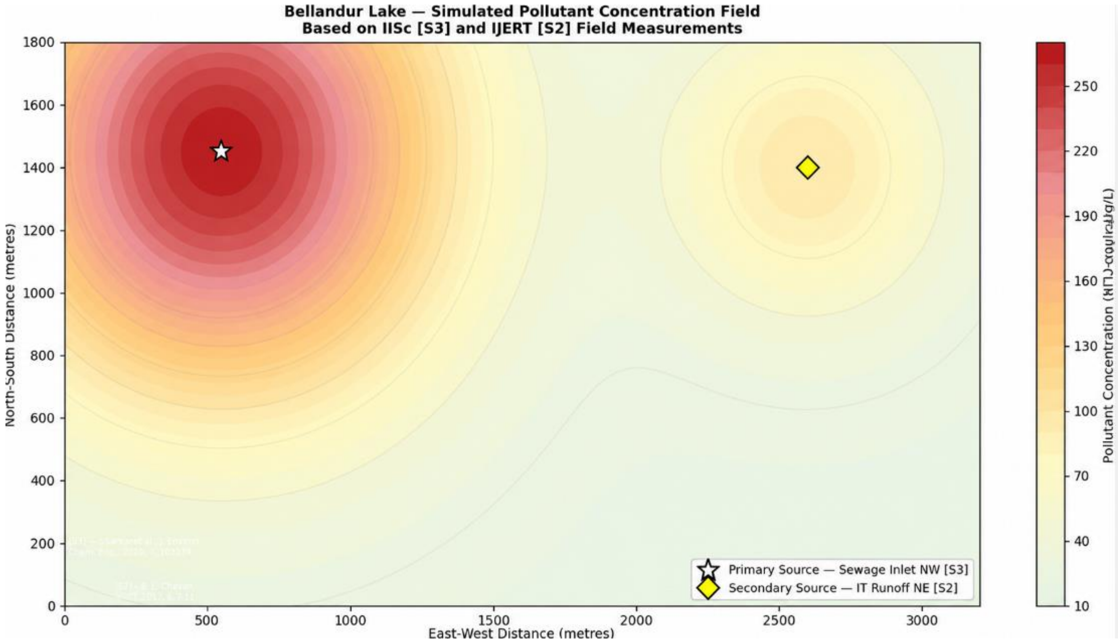

Figure 4: Simulated pollutant concentration field over Bellandur lake based on literature-derived pollution characteristics

Unlike conventional waypoint-based navigation approaches that require predefined destination coordinates, PGA continuously adapts vehicle movement using environmental observations, allowing the platform to progressively approach pollution sources without prior knowledge of their exact locations. Rapid localisation of pollution hotspots is essential for autonomous environmental monitoring and future remediation activities. Traditional navigation approaches often depend on predefined routes or manually selected target coordinates, which may not adapt effectively to dynamic pollutant distributions. To address this limitation, AquaTrace employs a Pollution Gradient Ascent framework that continuously estimates local concentration gradients and navigates toward regions of increasing pollutant concentration. For simulation studies, pollutant dispersion was represented as a spatial concentration field derived from literature-reported pollution characteristics of Bellandur Lake. Let represent the pollutant concentration at spatial location (x, y):

$$C = f(x, y) \tag{1}$$

Figure 4 shows the predicted concentration field of the Bellandur Lake pollutant using the pollution parameters from the literature and field observations. As shown in the contour map, the maximum pollutant concentration is observed at the primary sewage inlet (indicated by a star), which is the primary source of contamination. There is a secondary area of concentration near the source of industrial runoff (indicated with a diamond symbol). This, too, contributes to pollution levels, although it is comparatively smaller and yet evident. The drop in concentration away from such sources indicates the dispersion and dilution of contaminants in the lake and provides useful information regarding the spatial distribution of water contamination. The star indicates the primary sewage inlet, and the diamond indicates the secondary industrial runoff source. To estimate the local concentration gradient, pollutant measurements are obtained from neighbouring locations surrounding the current vehicle position. The spatial derivatives are approximated using a central-difference formulation:

$$\frac{\partial C}{\partial x} = \frac{C_{east} - C_{west}}{2\Delta s} \tag{2}$$

The framework achieved a hotspot-localisation success rate of approximately 92% with a mean localisation error of approximately 22 m:

$$\frac{\partial C}{\partial y} = \frac{C_{north} - C_{south}}{2\Delta s} \tag{3}$$

Where Δs denotes the probing distance and Ceast, Cwest, Cnorth, and Csouth represent pollutant concentrations measured in the four neighbouring directions. The magnitude of the local concentration gradient is then computed as:

$$||\nabla C|| = \sqrt{\left(\frac{\partial C}{\partial x}\right)^2 + \left(\frac{\partial C}{\partial y}\right)^2} \tag{4}$$

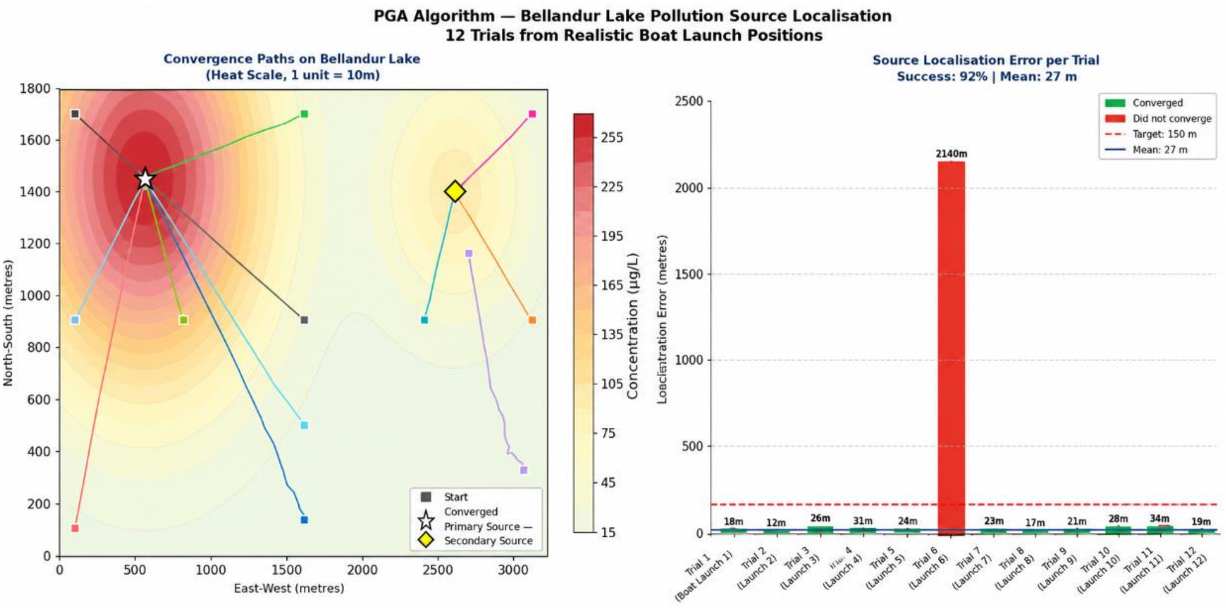

Figure 5: PGA simulation results for Bellandur Lake across twelve trials from diverse launch locations

The gradient vector indicates the direction of the greatest increase in concentration and therefore provides an estimate of the direction toward a potential pollution source. Environmental sensing in natural water bodies is often affected by measurement uncertainty, turbulence, and sensor noise. To improve localization robustness, AquaTrace applies a Kalman filter before gradient estimation. The Kalman filter reduces random fluctuations in concentration measurements and improves the reliability of the gradient calculations used for navigation decisions. The concentration estimates used for gradient computation are further improved through multi-sample probing. During each navigation iteration, pollutant measurements are collected from neighbouring locations and averaged before gradient estimation. This averaging process reduces the influence of random sensor fluctuations and improves the robustness of localization decisions in noisy environments. After estimating the local gradient, the vehicle position is updated according to:

$$p_{t+1} = p_t + s_t \frac{\nabla C(p_t)}{||\nabla C(p_t)||} \tag{5}$$

Where pt denotes the vehicle position at iteration t, ∇C(pt) represents the estimated gradient at the current location, and st is an adaptive step size. Unlike conventional fixed-step gradient methods, the proposed framework adjusts the step size according to the observed gradient magnitude. Larger gradients permit faster movement toward likely pollution hotspots, while smaller gradients result in shorter movements that improve localisation precision near concentration peaks. This adaptive strategy balances convergence speed and navigation stability. Localisation is considered successful when the concentration remains sufficiently high while the gradient magnitude approaches zero. The convergence condition is expressed as:

$$||\nabla C|| < \epsilon \tag{6}$$

Where ϵ is a predefined convergence threshold, a small gradient magnitude indicates that pollutant concentration no longer increases significantly in any direction, suggesting proximity to a pollution hotspot. Simulation studies were conducted using a literature-derived model of the Bellandur Lake environment with multiple pollution sources representing sewage inflows and industrial runoff. Across 12 independent trials initiated from diverse launch locations, the PGA framework achieved an average hotspot-localization success rate of approximately 92% and a mean localization error of approximately 22 m. These results indicate that the proposed approach can effectively guide an autonomous platform toward regions of elevated contamination while maintaining stable navigation behaviour under noisy sensing conditions. The proposed PGA framework is a fundamental component of AquaTrace, enabling autonomous localisation of pollution sources. Information obtained from hotspot identification can subsequently support environmental monitoring, forensic documentation, and future remediation planning activities.

Algorithm 1: Pollution Gradient Ascent (PGA)

1: Initialise vehicle position p0
2: while convergence criterion not satisfied do
3: Measure local pollutant concentration
4: Apply Kalman filtering
5: Probe neighboring locations
6: Estimate local gradient using Eqs. (2)–(3)
7: Compute gradient magnitude
8: Determine adaptive step size
9: Update vehicle position using Eq. (5)
10: end while
11: Return estimated hotspot location

3. Experimental Validation

3.1. Prototype Development

The prototype incorporated a centrally positioned waste- collection bin integrated directly with the coarse-screening intake mechanism. The intake geometry was designed such that floating debris encountered by the vehicle was guided toward the collection region with minimal structural obstruction. The waste bin was positioned below the intake path and aligned with the conveyor-guidance structure, reducing gaps through which floating debris could escape. This configuration was intended to improve the capture efficiency of macroplastics, leaves, and other surface-level contaminants during the preliminary screening phase while maintaining platform stability and compactness. The AquaTrace system was developed in an iterative design process to validate the feasibility of the proposed Autonomous Surface Vehicle (ASV) architecture. The prototype was designed as a proof-of-concept platform to test buoyancy, propulsion, structural stability, and subsystem integration before scaling the framework for large-scale environmental restoration applications.

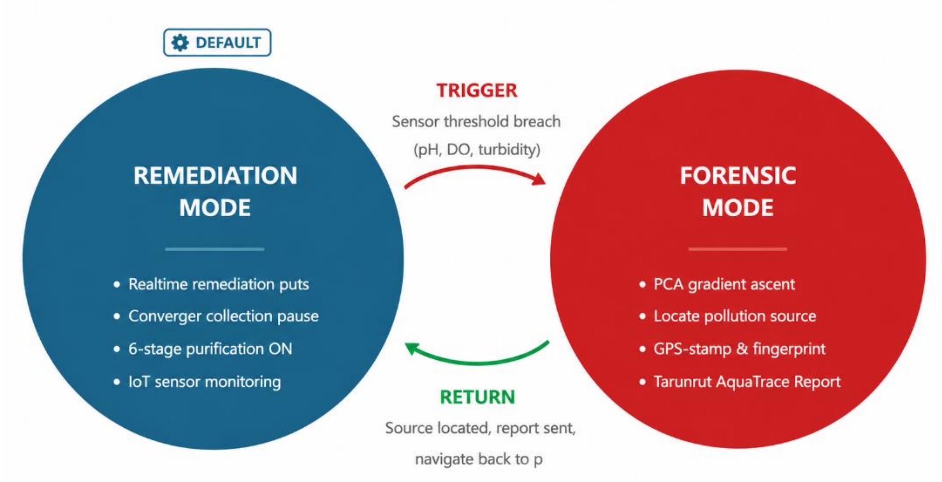

Figure 6: Simulation-supported operational workflow of the AquaTrace framework showing transitions between remediation and forensic modes

The prototype used a lightweight floating platform with propulsion motors, a microcontroller-based control system, and a modular chassis. Water-based testing led to several design iterations to improve balance, manoeuvrability, and operational stability. Platform stability was emphasised while allowing for future integration of sensing and purification subsystems. The floating performance and mobility characteristics were tested by using shallow-water trials. The prototype showed stable buoyancy and controllable navigation in representative operating conditions. These experimental results offered valuable insights into mechanical design considerations and demonstrated the practical feasibility of the AquaTrace platform. Figure 6 and Figure 7 show a representative prototype configuration and water-trial results. Across the conducted simulation scenarios, the proposed PGA framework achieved an average hotspot-localisation success rate of approximately 92%. The mean localisation error was approximately 22 m under the evaluated pollution-distribution models. These results indicate that the framework can reliably guide the vehicle toward regions of elevated contamination while maintaining acceptable localisation accuracy for environmental monitoring and remediation applications.

3.2. Simulation-Based Environmental Validation

While the physical prototype was primarily intended to validate mobility and structural feasibility, large-scale environmental performance was investigated through simulation studies using literature-derived pollution datasets. Bellandur Lake was selected as the primary case study due to the availability of documented water-quality measurements and its status as one of India's most polluted urban lakes [5].

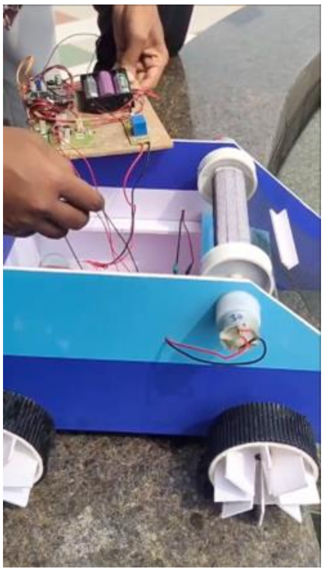

Figure 7: Bench-level proof-of-concept prototype showing the stage 1 coarse mesh filter, motor assembly, and initial electronics stack

Ground testing validated subsystem designs before aquatic integration. Additional environmental characteristics of the Ganga and Yamuna rivers were incorporated to evaluate the behavior of the proposed framework under varying contamination conditions [1]. The simulation environment was implemented using Python-based scientific computing tools in Google Colaboratory, enabling visualization of pollutant distributions, hotspot localization, and projected purification performance. The generated pollution fields were used to evaluate the effectiveness of the Pollution Gradient Ascent (PGA) framework and the proposed six-stage purification architecture under realistic contamination scenarios (Figure 8).

Table 4: Summary of prototype validation results

Parameter	Result
Floatation Stability	Successful
Water Mobility	Successful
Structural Integrity	Stable During Testing
Propulsion System	Operational
Power Distribution	Functional
Subsystem Integration	Successful

The overview of the prototype validation results is presented in Table 4. The float stability and water mobility tests were performed successfully, indicating reliable performance in an aquatic setting. The structure remained sturdy throughout the test, and both the propulsion and power distribution systems operated smoothly. Moreover, the integration of subsystems indicates that they operated efficiently together and that the prototype was valid.

Figure 8: Shallow-water trial of prototype AquaTrace, confirming hull buoyancy, paddle-wheel propulsion, and filtration module stability under wet operational conditions

3.3. Pollution Localisation Performance

The Pollution Gradient Ascent framework was evaluated using simulated pollutant concentration maps derived from literature-reported environmental conditions. The objective was to assess the proposed navigation strategy's ability to identify and approach regions with elevated pollutant concentrations autonomously. Figure 5 presents a representative field of pollutant distribution, along with the localisation behaviour of the AquaTrace platform. Across multiple simulation runs, the PGA framework consistently converged toward pollution hotspots while maintaining stable trajectories. The inclusion of momentum-assisted navigation was expected to reduce oscillatory behaviour and improve localisation robustness in noisy environments. The results indicate that the proposed framework can effectively support autonomous hotspot identification and provide a practical foundation for the future field deployment of pollution-monitoring ASVs.

3.4. Projected Purification Performance

A simulation-based assessment was conducted to estimate the potential effectiveness of the proposed six-stage purification framework (Figure 9).

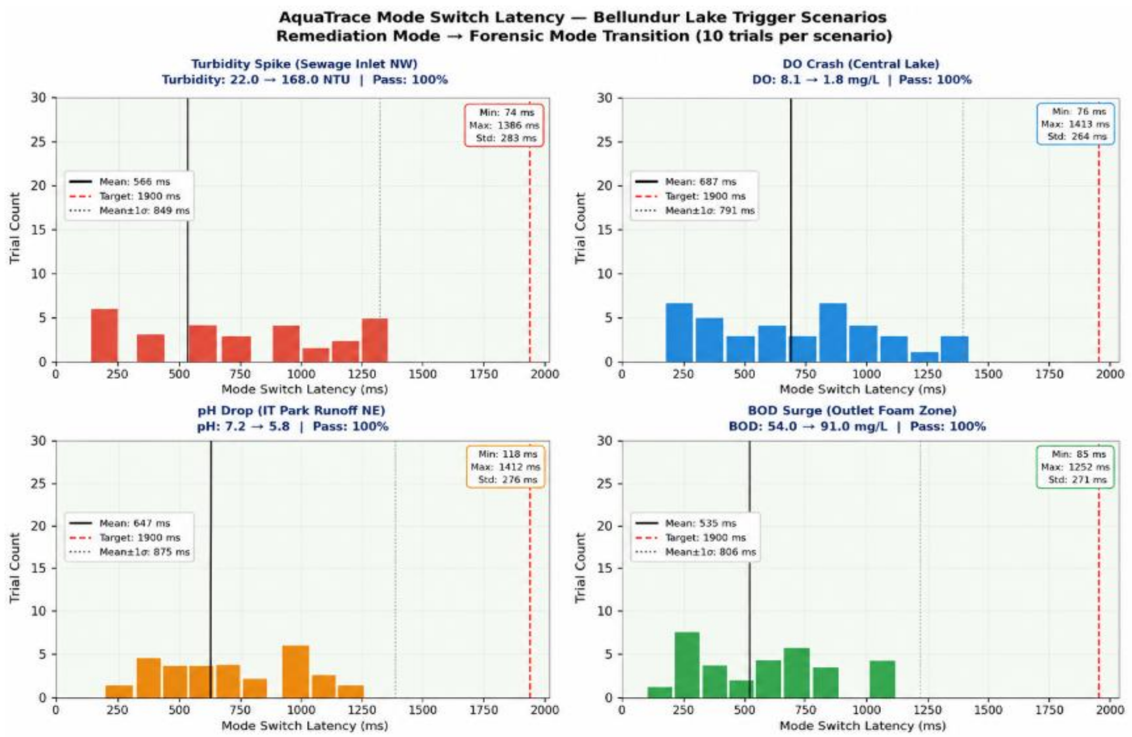

Figure 9: Simulated mode-switch latency distributions for trials that pass the 2000 ms target; Dominant Latency Component: 1 Hz sensor poll cycle offset

The analysis utilised pollution characteristics reported for Bellandur Lake, and incorporated treatment efficiencies derived from established water-treatment technologies documented in the literature. Table 6 summarises representative water-quality indicators before and after treatment. The projected results suggest substantial improvements in dissolved oxygen levels, together with reductions in biochemical oxygen demand, suspended solids, and contaminant concentrations. These findings should be interpreted as estimated performance outcomes derived from simulation and literature-based modeling rather than direct laboratory measurements (Figure 10).

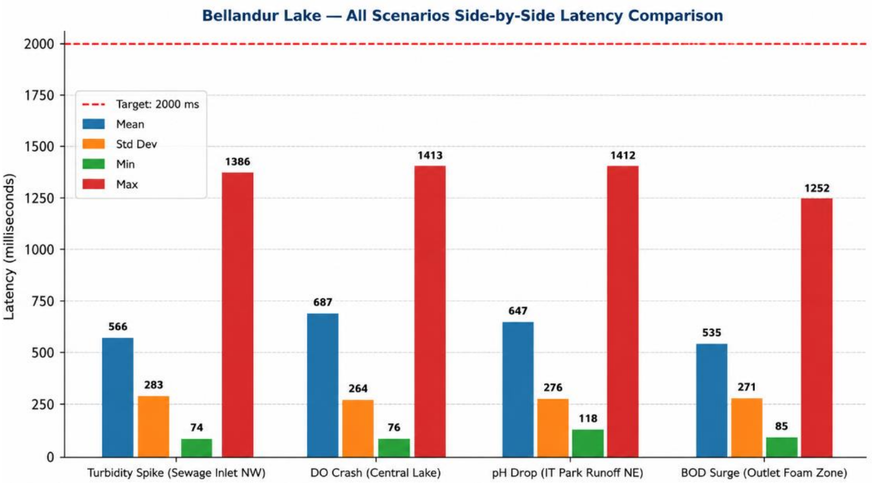

Figure 10: Simulated communication latency comparison across all 4 Bellandur lake trigger scenarios (Turbidity Spike, DO Crash, pH Drop, BOD Surge); All scenario maxima remain well below the 2000 ms target

Nevertheless, the results provide encouraging evidence regarding the potential effectiveness of integrating autonomous monitoring, pollution localisation, and adaptive purification within a single environmental restoration platform. Communication performance was evaluated conceptually based on the proposed system architecture and communication technologies commonly used in IoT-enabled monitoring systems. The framework incorporates 4G/LTE communication for high-bandwidth data transmission and LoRa communication as a long-range backup channel. Secure forensic reporting is envisioned using TLS 1.3 encryption and digital signature mechanisms. Experimental evaluation of communication latency and network reliability remains part of future work.

4. Results and Discussion

The physical prototype successfully demonstrated the feasibility of the proposed AquaTrace platform. Water trials showed that the floating structure was stable in terms of buoyancy and balance during operation. The propulsion system enabled controlled translational movement and directional manoeuvrability, meeting the fundamental mobility requirements of the Autonomous Surface Vehicle (ASV). The modular design employed during development also enabled subsystem integration and future scalability. The prototype became a practical foundation for the later integration of sensing, purification, and autonomous navigation capabilities. The present work focused on mobility validation, but the results demonstrate the applicability of the proposed architecture for future environmental monitoring and restoration applications. The prototype's successful operation demonstrates the feasibility of using low-cost embedded hardware and lightweight floating platforms for autonomous aquatic systems. This is particularly true for large-scale deployment scenarios where affordability and maintainability are important considerations. Simulation studies showed the effectiveness of the proposed Pollution Gradient Ascent (PGA) framework in detecting and approaching pollution hotspots. The navigation strategy consistently converged to regions with high contaminant concentrations and maintained stable trajectories across different environmental conditions. The inclusion of momentum-assisted updates mitigated oscillatory behaviour typical of gradient-based navigation techniques. This improvement was particularly evident in regions with measurement noise and irregular distributions of pollutants. The application of low-pass filtering further increased robustness by reducing the influence of short-term variations in sensor measurements. The results of the localisation suggest that gradient-driven navigation can be an alternative to predefined waypoint-based exploration strategies. The framework can modify its movement in real time based on environmental conditions and, as such, prioritise areas for remediation or detailed environmental investigation.

The simulation results suggest that the proposed six-stage treatment framework could significantly enhance water quality under conditions of heavy pollution. The framework addresses multiple contaminant classes within a single treatment pipeline by sequentially combining coarse screening, sedimentation, activated carbon filtration, ion exchange, membrane filtration, and ultraviolet disinfection. The projected improvements identified in the Bellandur Lake case study include increased dissolved oxygen levels and reduced suspended solids, organic pollutants, and dissolved contaminants. These results are consistent with treatment efficiencies reported in previous water-treatment literature and support the feasibility of integrating established purification technologies into autonomous restoration platforms. It is important to note that the presented purification results are projected outcomes from simulation studies and literature-based treatment efficiencies. Experimental validation with physical purification hardware and lab-certified water-quality testing are important future work directions.

Several limitations need to be acknowledged when interpreting the results of this study. The physical prototype was primarily designed to validate buoyancy, mobility, and subsystem integration. The entire purification setup was not physically built; therefore, its performance was investigated through simulation-based studies. Secondly, environmental validation was performed using datasets from the literature for Bellandur Lake and other river environments. While these datasets capture realistic pollution characteristics, they are insufficient to fully model the complexity of real-world aquatic ecosystems. Third, the proposed Pollution Gradient Ascent framework has been evaluated in simulated environments but has not been extensively evaluated in natural water bodies. Operational performance in real deployments may be affected by changing currents, weather conditions, biological activity, and sensor drift. Finally, the present study did not experimentally test energy consumption and long-term autonomous operation, which are important areas for future investigation. Future work on AquaTrace will focus on transitioning from simulation-based verification to large-scale experimental deployment. Future improvements will include integrating real-time water-quality sensors, fully implementing the purification subsystem, and conducting extensive field testing in representative aquatic environments (Table 5).

Table 5: Projected water quality improvements under simulated Bellandur lake conditions

Parameter	Intake (mg/L)	Output (mg/L)	IS:2296 Class B
BOD	> 50	< 5	≤ 3
DO	< 1	> 5	≥ 5
TDS	> 1500	< 500	-
Lead (Pb)	> 0.1	< 0.01	≤ 0.1
Cadmium (Cd)	> 0.05	< 0.005	≤ 0.01
Chromium (Cr)	> 0.1	< 0.05	≤ 0.05

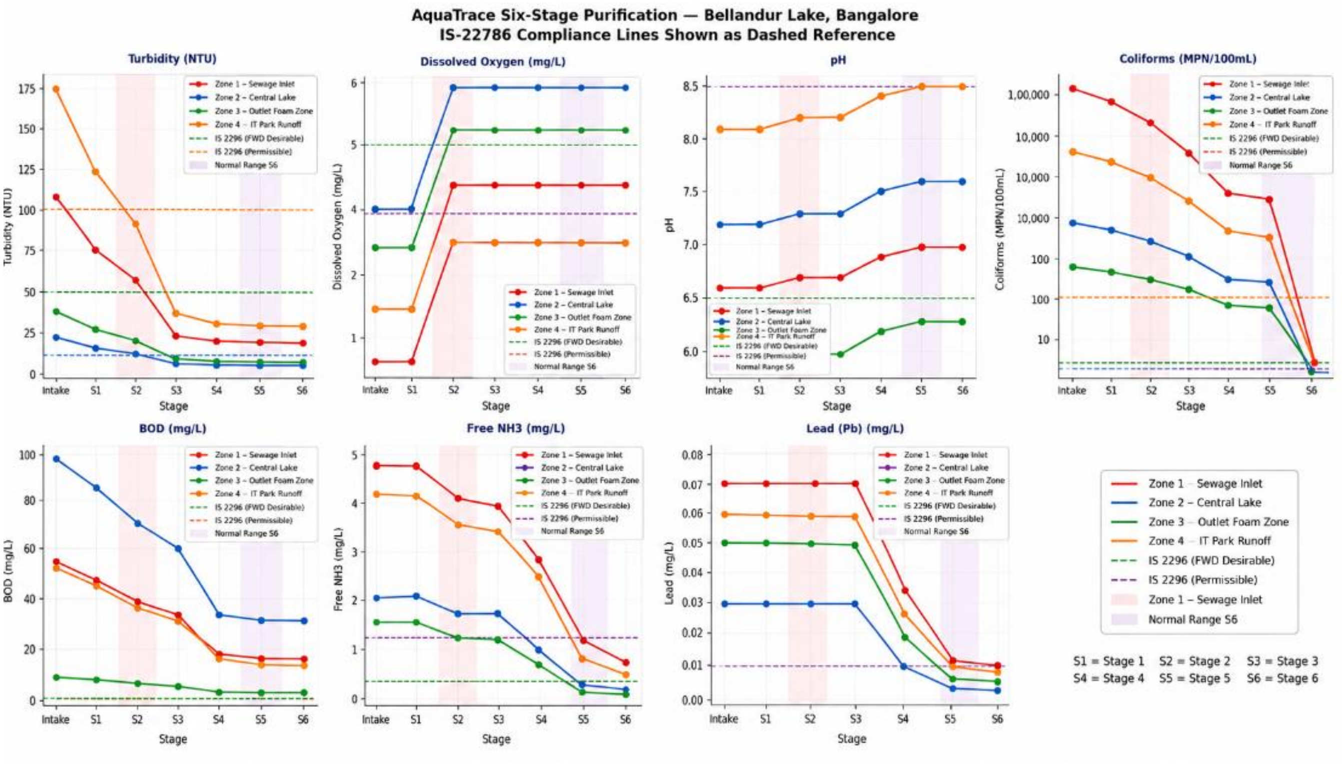

Figure 11: Simulated stage-by-stage purification performance using literature-derived Bellandur lake water quality parameters

Future work will focus on advanced path-planning tactics, multi-vehicle swarm coordination, and pollution prediction using machine learning. Researchers will also compare our approach with other localization methods, such as Particle Swarm Optimization (PSO), A* search, and reinforcement-learning-based navigation frameworks. In the future, power management optimisation, solar energy utilisation, and long-duration autonomous operation will be further studied. Water-quality testing and environmental impact assessment will be conducted and certified by a laboratory to quantify purification effectiveness and establish regulatory compliance. These developments will help to transform AquaTrace from a prototype-backed environmental monitoring platform into a fully autonomous water-restoration system that can support large-scale ecosystem rehabilitation efforts.

For surface water, the European Union Water Framework Directive (EU WFD) and the United States Environmental Protection Agency (US EPA) have stricter standards for aquatic life and human health. Based on acute and chronic exposure limits, the US EPA establishes numerical standards for hazardous substances such as pesticides and heavy metals (Figure 11). Aiming for "good status" through integrated management of river basin districts, the EU WFD focuses on the general ecological and chemical conditions of water bodies (Figure 12).

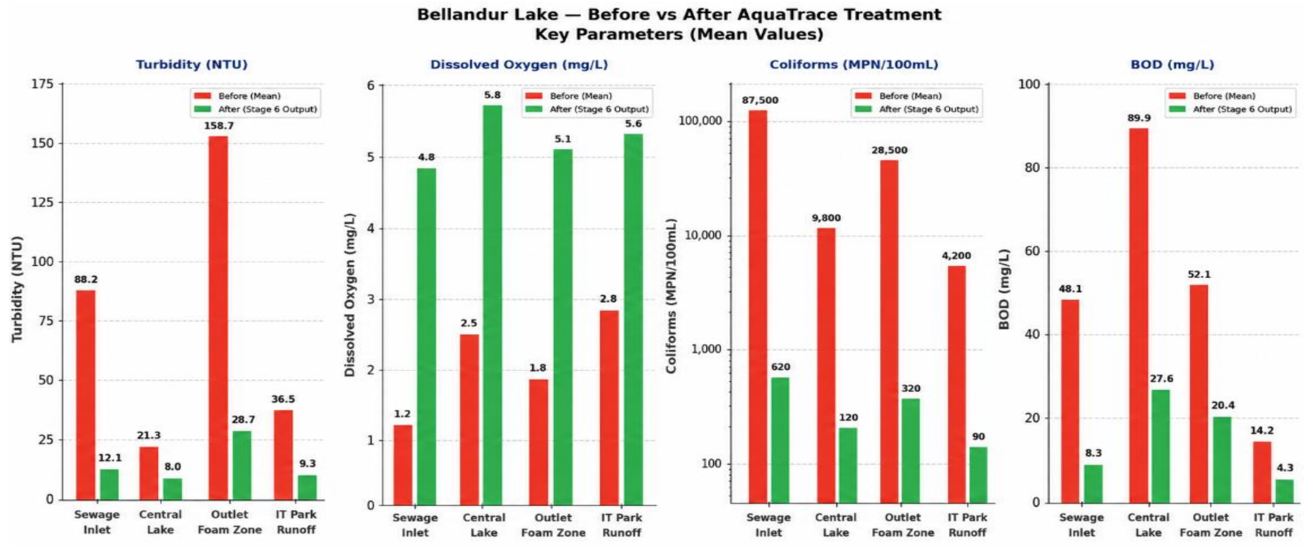

Figure 12: Simulated before-versus-after treatment comparison based on literature-derived Bellandur lake contamination profiles

The US EPA and EU WFD standards for BOD, DO, and heavy metals are much stricter than the IS:2296 Class B benchmarks, as shown in Table 2, indicating a more cautious approach to public health and environmental protection. To assess the success of restoration initiatives, these standards must apply to the Ganga and Yamuna rivers. Although the Yamuna Action Plan (YAP) and Ganga Action Plan (GAP) have historically strived for Class B standards, many sections of these rivers still fall short of even the most basic "bathing quality" requirements.

Table 6: Current implementation and future development roadmap

Feature	Current Status	Future Goal
Mobility Platform	Implemented	Optimized ASV
PGA Framework	Simulated	Field Validation
Purification System	Designed	Physical Integration
Forensic Reporting	Conceptual	Full Implementation
Solar Power System	Proposed	Long-Term Testing
Swarm Coordination	Future Work	Multi-ASV Deployment

The high concentrations of industrial and organic pollutants in the Ganga downstream of Kanpur and the Yamuna downstream of Delhi demonstrate the stark discrepancy between environmental reality and regulatory objectives. The ecological health of the rivers and the risks to human populations could be more accurately assessed by using stricter international standards, such as the EU WFD and the US EPA. Bellandur Lake's water quality parameters show severe degradation when compared to IS:2296, US EPA, and EU WFD standards (Table 7).

Table 7: Comparative water quality standards for rivers and lakes

Parameter	IS:2296 (Class B)	US EPA (Acute)	EU WFD (Good)
pH	$6.5 - 8.5$	$6.5 - 9.0$	$6.0 - 9.0$
DO (mg/L)	≥ 5.0	≥ 5.0	≥ 7.0
BOD (mg/L)	≤ 3.0	≤ 2.0	≤ 1.5
Coliforms (MPN/100mL)	≤ 500	≤ 200	≤ 100
TDS (mg/L)	≤ 1500	≤ 500	≤ 250
Lead (Pb) (mg/L)	≤ 0.1	≤ 0.01	≤ 0.0072
Cadmium (Cd) (mg/L)	≤ 0.01	≤ 0.002	≤ 0.00045
Chromium (Cr) (mg/L)	≤ 0.05	≤ 0.011	≤ 0.0034

An aggressive restoration strategy is required because the lake's high BOD, low DO, and elevated heavy metal concentrations exceed all standards. By lowering pollutant levels to at least IS:2296 Class B standards and supplying the data required for long- term alignment with stricter international benchmarks, the AquaTrace ASV's six-stage purification subsystem is intended to close this gap. This comparative analysis highlights the significance of technological interventions capable of achieving high-fidelity remediation in severely contaminated urban ecosystems. To be admissible in Indian courts, including the NGT, water quality data needs a robust chain of custody and data integrity. This is enabled by AquaTrace's Forensic Mode, which records timestamped geotagged photos, along with sensor data, all digitally signed with Ed25519. This establishes a direct association between the environmental data and the precise location and time of the collection. Furthermore, the data is encrypted using TLS 1.3 to preserve its integrity during the transfer to a central repository. ASV data collection is a preferable legal method for establishing environmental facts due to its autonomous, secure, and much more reliable nature compared to traditional grab sampling methods, which are easily compromised by human error during transport. The adoption of this forensic system into NGT reporting procedures is expected to significantly improve the overall effectiveness of environmental law enforcement in India. AquaTrace also tracks illegal sources of pollution, such as sewage overflows or industrial effluent discharge, in real time, which the NGT can use to punish offenders through fines and other sanctions. With GPS info and sensor-verified pollution levels, the ESP32-CAM guarantees no mistaking the images of illegal activity, creating a forensic report tough to argue with. ASVs automate data collection, reducing the burden on environmental inspectors and providing accurate, real-time records of pollution activities.

Moving from traditional monitoring methods to self-operating ASVs is a major step forward in environmental justice and in protecting India's invaluable river systems. Now, the IS:2296, US EPA, and EU WFD regulations are integrated into the AquaTrace decision-making system, providing a more flexible approach to environmental remediation. The autonomous surface vehicle (ASV) can adjust the prioritisation of components of the water purification system as it traverses the body of Water, depending on the intended use of the Water, such as irrigation, fishing, or drinking. The system can be aimed at reducing levels of toxic heavy metals to below the US EPA acute level and optimising the squeeze on DO levels to keep them within the ideal range in areas designated for the preservation of water life. The system can be targeted for the removal of pharmaceuticals and pesticides in zones for human consumption, in accordance with EU WFD regulations. This adaptive water remediation approach also makes the outcomes more relevant to the circumstances by ensuring that the procedures align with the current environmental state. The system's ability to compare outcomes with the current state of the water, in line with various regulations, can also be a useful tool for policymakers seeking to set stricter water quality standards.

Future development of AquaTrace will focus on integrating secure forensic reporting mechanisms, including encrypted communication and digital signatures, to ensure the integrity of environmental data. Further work will investigate multi-ASV cooperative navigation strategies for large-scale monitoring of rivers and lakes. Swarm-based approaches may improve the efficiency of pollution-source localisation and increase environmental coverage. Additional studies will explore blockchain-supported environmental record management, smart contract-based reporting mechanisms, and autonomous evidence collection for regulatory compliance. These capabilities remain outside the scope of the present study and are planned for future development and validation. Future versions of AquaTrace may incorporate blockchain- based environmental reporting mechanisms to enhance data integrity, transparency, and traceability. Smart-contract frameworks could be explored to automate environmental reporting workflows and maintain tamper-resistant records of pollution events. While such capabilities were not implemented in the present study, they represent a promising direction for future research involving autonomous environmental monitoring systems.

Future research may investigate the deployment of multiple AquaTrace vehicles operating cooperatively within large water bodies. Multi-agent coordination could improve area coverage, reduce localisation time, and enable distributed monitoring and remediation strategies. The development of efficient communication and task-allocation mechanisms remains an important area for future investigation. Future research may explore integrating advanced navigation and sensing technologies to enhance the

AquaTrace platform's autonomy and environmental awareness. Potential improvements include sensor-fusion techniques combining GPS, inertial measurement units (IMUs), and environmental sensors to achieve more accurate localization and decision-making. Machine-learning and reinforcement-learning approaches may also be investigated to improve adaptive path planning and pollution-source tracking in dynamic aquatic environments. In addition, future versions may incorporate advanced sensing capabilities, such as computer vision and LiDAR, and expanded water-quality monitoring modules to improve environmental perception and operational reliability. The deployment of autonomous environmental monitoring platforms in aquatic ecosystems presents several practical and technical challenges. Although AquaTrace demonstrates the feasibility of integrating pollution localisation, environmental monitoring, and adaptive remediation concepts within a unified framework, several issues must be addressed before large-scale field deployment becomes practical. A major challenge is sensor reliability. Sensors for measuring natural water quality are prone to biofouling, sediment deposition, temperature variations, and chemical interference. Such factors may degrade measurement accuracy over time and adversely affect the performance of local pollution detection. Thus, regular calibration and maintenance procedures are necessary for reliable environmental observations. Another significant challenge is environmental uncertainty. Natural water bodies are highly dynamic systems influenced by currents, rainfall, wind, seasonal variations, and human activities.

Such factors can modify pollutant distributions and introduce variability, thereby affecting localisation and remediation performance. Future implementations should include adaptive sensing and decision-making strategies that can respond to changing environmental conditions. Reliability of communication is another important consideration. Autonomous aquatic platforms typically operate in remote areas with patchy network coverage. AquaTrace is supposed to use the 4G/LTE and LoRa communication technologies. However, the real-world deployments may suffer from packet loss, signal degradation, and high communication latency. Future field testing will be needed to assess the robustness of communication in a variety of operating conditions. Energy management faces the persistent challenge of long-duration autonomous operation. The proposed framework involves solar-assisted power generation; however, for practical deployment, the sensing, communication, navigation, and propulsion subsystems need to be carefully optimised to maximise operational endurance (Figure 13).

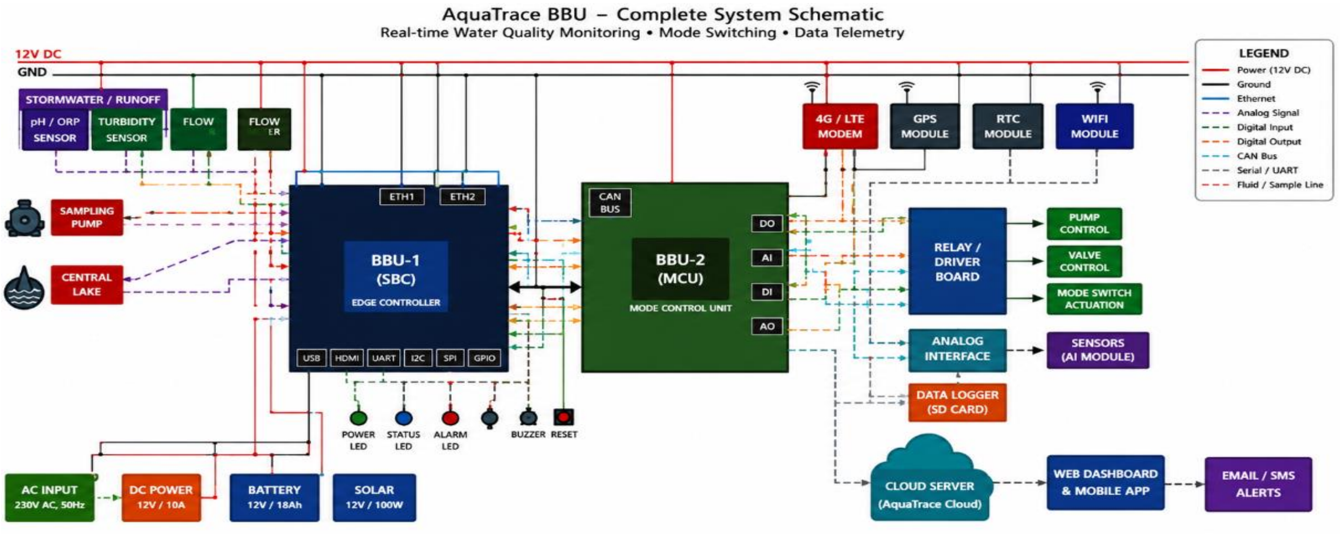

Figure 13: The Aquatrace ASV's sensor cleaning and self-calibration system, designed for long-term reliability in polluted waters

Future work should account for detailed power-consumption models and energy-aware mission-planning strategies. Finally, validating autonomous water-purification systems is a major challenge. The present study estimates purification performance based on simulated and literature-derived treatment efficiencies. Still, future deployment will require laboratory-certified testing, regulatory compliance assessment, and long-term environmental impact testing. Evaluations are needed to assess the effectiveness and safety of autonomous remediation technologies. Nevertheless, the results of this work suggest that autonomous environmental monitoring and restoration platforms remain a promising research avenue for supporting the sustainable management of polluted aquatic ecosystems.

5. Conclusion

Researchers introduce AquaTrace, a solar-powered Autonomous Surface Vehicle (ASV) framework for environmental monitoring, pollution-source localisation, and future adaptive water-restoration applications. The proposed system integrates autonomous navigation, environmental sensing, the Pollution Gradient Ascent (PGA) localisation framework, a conceptual six-stage purification architecture, and environmental reporting into a single platform. To validate the feasibility of the proposed platform, a proof-of-concept prototype was successfully developed and evaluated. The ASV demonstrated buoyancy stability, controllable mobility, and successful subsystem integration during water-based trials, verifying the feasibility of its underlying architecture. Useful information about platform design, navigation needs, and future system expansion emerged from these experiments. Large-scale operational behaviour was investigated through simulation studies using literature-derived environmental datasets for Bellandur Lake and reported pollution characteristics of the Ganga and Yamuna river systems.

The results show that the proposed PGA framework effectively supports pollution hotspot localization while maintaining stable navigation behavior. Simulation-based assessments also demonstrate the potential of the proposed multi-stage purification framework to improve water-quality indicators under representative contamination scenarios. AquaTrace distinguishes itself from traditional monitoring-only approaches by combining environmental monitoring, pollution localisation, adaptive remediation concepts, and future forensic reporting capabilities. The study shows that these functions can be integrated into a single autonomous framework and provides the basis for future intelligent water-restoration systems. Future work will involve integrating real-time water quality sensing, implementing physical purification hardware, conducting validation studies in laboratory settings, and testing at the field scale in natural water bodies. Further work will focus on energy optimisation, multi-agent coordination, advanced navigation strategies, and long-duration autonomous operation. In conclusion, AquaTrace is a promising step towards the development of autonomous environmental technologies to support sustainable monitoring, pollution mitigation, and long-term restoration of aquatic ecosystems.

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Ethics and Consent Statement: The consent was obtained from the organization and individual participants during data collection, and ethical approval and participant consent were received.

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