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IoT and GSM-Enabled Smart Agricultural System for Automated Irrigation and Environmental Monitoring using Raspberry Pi

Ajay Rameshwar Ambade¹, Prof. M. R. Bendre²

Student, VACOE, Ahmednagar, India¹ Professor, VACOE, Ahmednagar, India²

ABSTRACT: The increasing pressure on freshwater ecosystems caused by urban expansion, industrial effluents, agricultural runoff, and climate variability has led to significant deterioration in river water quality and disrupted natural hydrological patterns. Traditional river monitoring methods—based on manual sampling and laboratory testing—are often limited in scalability, delayed in response time, and ineffective for real-time environmental decision-making. This paper proposes an Internet of Things (IoT)-based system for continuous river water quality and quantity monitoring, leveraging Raspberry Pi (RPI) as the core processing unit. The system integrates multiple environmental sensors—such as pH, turbidity, temperature, dissolved oxygen, and flow sensors—directly connected to the RPI, which collects and processes real-time data from the river environment. To ensure remote accessibility and dynamic visualization, the monitored data is transmitted to the ThingSpeak cloud platform, where it is rendered in the form of real-time graphs and visual dashboards. This setup allows environmental agencies and stakeholders to continuously track water quality trends, detect potential pollution events, and make informed, data-driven decisions. The system is designed to be energy-efficient and is powered by a solar-based power supply, ensuring uninterrupted operation in remote or off-grid river locations. The inclusion of GIS mapping and satellite integration enhances the geospatial context of the data. By providing continuous, accurate, and accessible monitoring, this IoT-based solution represents a scalable and sustainable approach for protecting river ecosystems and supporting water resource management.

KEYWORDS: River Monitoring, Water Quality, Real-time Data, Environmental Sustainability, Pollution Detection. ThingSpeak

I. INTRODUCTION

Freshwater ecosystems, particularly rivers, are fundamental to ecological stability and socio-economic development. They provide essential services such as potable water supply, irrigation, transportation, fisheries, and industrial support while also maintaining the hydrological cycle and biodiversity. However, with the advent of rapid urbanization, intensive agriculture, industrialization, and erratic climate patterns, rivers are under increasing pressure. These stressors contribute to the degradation of water quality, alteration of natural flow regimes, and frequent pollution events, posing significant risks to both aquatic life and human health. The impacts are especially pronounced in developing regions where infrastructure for real-time monitoring and regulation is either insufficient or altogether absent.

Traditional river water monitoring practices have primarily relied on manual sampling followed by laboratory-based chemical and biological analysis. Although accurate, these methods are constrained by spatial and temporal limitations, offering only periodic snapshots of water quality rather than continuous insights. They are also labor-intensive, time-consuming, and expensive to maintain, especially across long river stretches or in remote locations. Consequently, this limited monitoring capability delays the detection of contamination or harmful fluctuations in flow rate, resulting in ineffective or late-stage interventions. To address these gaps, there is a critical need for automated systems that offer high-resolution, real-time environmental monitoring at scale.

Recent advances in embedded systems, low-power sensors, wireless communication, and cloud computing have enabled the development of Internet of Things (IoT)-based solutions for environmental applications. IoT systems facilitate the real-time acquisition, transmission, storage, and visualization of data from distributed sensor nodes. In the context of river monitoring, these systems can be deployed to continuously track key parameters such as pH, turbidity,





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temperature, dissolved oxygen, and conductivity. By deploying sensors at multiple points along a river and using centralized cloud platforms for visualization and analysis, authorities can gain a comprehensive view of the river's condition. This data-centric approach supports better decision-making, faster response to environmental anomalies, and long-term trend analysis.

This research proposes the design and implementation of an IoT-enabled river water monitoring system using Raspberry Pi as the central control unit. Various water quality sensors are interfaced with the Raspberry Pi, which processes and uploads real-time data to the ThingSpeak cloud platform for graphical visualization. The system also integrates solar power to ensure energy autonomy, making it suitable for deployment in remote and off-grid locations. The solution emphasizes affordability, modularity, and ease of deployment while maintaining the technical rigor required for reliable environmental monitoring. By addressing the critical shortcomings of manual monitoring systems, this project aims to contribute a scalable, sustainable, and replicable model for river conservation and intelligent water resource management.

II. METHODOLOGY

The core methodology of this project involves the deployment of an Internet of Things (IoT)-based river monitoring system that continuously measures key water quality parameters using a distributed network of environmental sensors. At the heart of the system lies a Raspberry Pi microcontroller, which acts as a local data acquisition and processing hub. Multiple sensors—including those for pH, turbidity, temperature, and dissolved oxygen—are interfaced directly with the Raspberry Pi through analog-to-digital converters or digital communication protocols such as I2C and UART. These sensors are placed in waterproof enclosures and submerged at designated monitoring points along the riverbank. The Raspberry Pi collects data from each sensor at predefined intervals, stores it temporarily in local memory, and initiates data transmission to a remote server using a Wi-Fi or cellular module, depending on the site's network availability. The entire sensing node is powered using a solar panel and a rechargeable battery system, ensuring uninterrupted functionality even in off-grid environments.

To enable real-time monitoring and data visualization, the system is integrated with the ThingSpeak IoT cloud platform. This platform is used for storing, analyzing, and visualizing the sensor data in graphical formats such as line charts and bar graphs. The Raspberry Pi is configured to publish data to ThingSpeak using its API interface. Each sensor parameter is assigned a dedicated channel on the platform, allowing stakeholders to monitor real-time fluctuations and historical trends through a web-based dashboard. ThingSpeak also supports threshold-based triggers, enabling the generation of automated alerts via email or SMS when any parameter exceeds pre-defined safe limits. This capability ensures timely detection of environmental anomalies such as sudden pollution events or oxygen depletion, which could pose risks to aquatic ecosystems or water usability for downstream applications.







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The system architecture has been designed with modularity and scalability in mind, making it adaptable to different river systems and environmental conditions. The hardware is housed in weatherproof enclosures (IP67 rated) to withstand harsh outdoor conditions, while the software stack is developed using Python scripts on the Raspberry Pi for sensor data acquisition and HTTP requests to the cloud. For ease of maintenance and scalability, the system supports plug-and-play sensor replacement and allows additional parameters—such as electrical conductivity or ammonia levels—to be added as needed. Furthermore, the integration of Global Positioning System (GPS) modules and optional GIS tools provides geolocation data, enabling spatial mapping of pollution sources and water quality gradients across different monitoring sites. The comprehensive methodology ensures that the system is not only effective in capturing real-time environmental data but also reliable, low-cost, and suitable for long-term deployment in a wide range of geographical and climatic conditions.

III. DATA COLLECTION AND SENSOR DEPLOYMENT

The data collection process for this river water monitoring system is built around a modular, IoT-enabled architecture designed to perform continuous, on-site measurement of key water quality indicators. The foundation of the system lies in the integration of a Raspberry Pi microcontroller, which acts as the primary control unit and is responsible for interfacing with multiple environmental sensors. Each sensor is tasked with capturing a specific parameter: the pH sensor measures the acidity or alkalinity of the water, the turbidity sensor quantifies water clarity and suspended particles, the dissolved oxygen (DO) sensor monitors oxygen levels critical to aquatic life, and the temperature sensor tracks thermal variations that affect biological and chemical processes in the river. These sensors are strategically positioned at selected monitoring points along the river to capture a representative sample of the aquatic environment. Their placement is influenced by factors such as proximity to industrial discharge zones, agricultural runoff points, and areas of stagnant or flowing water.

To ensure accurate and noise-free data collection, sensors are interfaced with the Raspberry Pi using appropriate analog-to-digital converters (ADCs), such as the MCP3008, when dealing with analog outputs, or directly through I2C/UART interfaces for digital sensors. The system collects sensor data at regular time intervals, typically every few minutes, which allows for the detection of short-term fluctuations as well as the aggregation of long-term trends. Each sensor is calibrated periodically to maintain accuracy, and the physical sensor units are enclosed in waterproof housings to prevent damage from prolonged submersion and debris accumulation. The Raspberry Pi unit itself is mounted in a weatherproof enclosure with proper thermal ventilation and protected from environmental elements like rain, humidity, and dust. The entire setup is supported by a solar panel and battery module to provide uninterrupted operation in remote or off-grid locations, making the system autonomous and ideal for field deployments without the need for frequent human intervention.

Sensor data is initially processed locally on the Raspberry Pi, which formats the readings and logs them before transmitting the data to the cloud. For cloud integration and visualization, the ThingSpeak platform is utilized due to its compatibility with embedded devices and its support for real-time data rendering through web-based dashboards. Data is pushed to individual ThingSpeak channels using HTTP POST requests or MQTT protocol. Each channel corresponds to a specific sensor or monitoring point, enabling clear organization and traceability of readings. The use of ThingSpeak also facilitates the setup of alerts when predefined water quality thresholds are crossed, ensuring timely notifications to relevant stakeholders. Additionally, the deployment strategy allows for scalability—more sensor nodes can be added across different sections of the river, forming a distributed monitoring network. This spatially diverse data collection method enables comprehensive analysis of water quality variability along the river's course and supports decision-makers in identifying pollution sources and implementing localized mitigation strategies.

IV. PREDICTIVE ANALYTICS AND ANOMALY DETECTION

Predictive analytics and anomaly detection in the proposed river water monitoring system are primarily performed using rule-based algorithms, threshold logic, and statistical methods directly applied to the real-time sensor data collected from the field. Since the system continuously monitors parameters such as pH, turbidity, dissolved oxygen, and temperature, it is possible to establish a baseline operating range for each parameter based on historical trends and environmental standards (e.g., Central Pollution Control Board norms). Any data points that deviate significantly from this predefined range are flagged as anomalies. For example, a sudden drop in dissolved oxygen levels below 4 mg/L or





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a turbidity spike above 50 NTU could indicate contamination, industrial discharge, or sediment influx. These thresholdbased conditions are programmed directly into the Raspberry Pi or evaluated through ThingSpeak's inbuilt data analysis capabilities using MATLAB visualizations and conditional alerts.

To enhance reliability, the system applies moving average and standard deviation filters to smooth the sensor readings and eliminate outliers caused by noise or transient disturbances. A rolling window-based approach is used to continuously compute average values over a predefined number of previous samples—typically 5 to 10 readings. This not only filters out momentary spikes but also allows the system to identify gradual deviations from normal conditions. For instance, a slowly decreasing trend in pH or DO over several hours can be interpreted as a developing issue, even if the individual values are not immediately alarming. These trend-based evaluations provide early warning insights to stakeholders, allowing them to take preventive measures before the situation escalates. Additionally, these techniques are computationally lightweight, making them ideal for processing directly on the Raspberry Pi without requiring cloud-side machine learning models.

In the event of a detected anomaly or when sensor readings approach critical thresholds, the system generates immediate alerts and publishes them to the ThingSpeak platform. In future through ThingSpeak's alerting service, SMS or email notifications can be sent to registered users or monitoring authorities. Each alert includes a timestamp, sensor ID, type of violation, and the actual sensor value that triggered the warning. These alerts are essential for real-time response, especially in cases where pollution events could affect downstream water users or aquatic biodiversity. Moreover, all sensor data and associated alerts are logged and time-stamped for future analysis, enabling the generation of summary reports that can be reviewed weekly or monthly. This logic-based approach, although simpler than machine learning, is highly effective for real-time anomaly detection and predictive trend estimation, offering a practical and reliable solution for environmental monitoring where computational resources are limited and interpretability is critical.

V. VISUALIZATION

Graph-based visualization is a core feature of the proposed IoT river monitoring system, allowing real-time interpretation of sensor data in an intuitive and accessible format. Each environmental parameter—such as pH, turbidity, temperature, and dissolved oxygen—is plotted on dynamic, time-series graphs through the ThingSpeak platform. These graphs are continuously updated as the Raspberry Pi transmits new readings, providing live feedback on the condition of the river at each monitoring point. The x-axis of the graph represents time in configurable intervals (e.g., minutes, hours, days), while the y-axis represents the value of the selected parameter. These visualizations enable stakeholders to monitor fluctuations over short and long durations, identify unusual behavior such as sharp spikes or drops, and evaluate environmental stability. For example, if a sudden drop in dissolved oxygen is observed on the graph, it could indicate organic contamination or stagnation, prompting immediate attention from relevant authorities.

The use of color-coded lines and comparative graphing enhances the clarity of multi-parameter analysis. Multiple sensor values can be visualized concurrently on a shared timeline, allowing users to identify relationships between parameters—for instance, how increasing turbidity may correlate with decreasing dissolved oxygen levels. Additionally, threshold lines can be added to the graphs to mark safe and critical operating zones, making it easy to distinguish between normal and alarming conditions at a glance. Historical data stored on ThingSpeak is also accessible through the graph interface, enabling the generation of monthly or seasonal trends. These graphical representations not only serve operational monitoring purposes but also support academic research, environmental auditing, and policy formulation by providing transparent, high-resolution insight into river health over time.

VI. HARDWARE DESIGN

The hardware design of the IoT-based river water monitoring system centers around a robust and modular sensing node architecture that enables precise and continuous environmental data acquisition. At the core of each sensing node is a Raspberry Pi microcontroller (preferably Raspberry Pi 4 Model B), selected for its high processing capability, multiple GPIO ports, and compatibility with various communication protocols such as I2C, SPI, UART, and USB. This microcontroller serves as the central processing hub, interfacing with a suite of water quality sensors that include a pH sensor, turbidity sensor, temperature sensor, and dissolved oxygen (DO) sensor. These sensors are selected based on





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their sensitivity, durability, and compatibility with outdoor, submerged conditions. For analog sensors, MCP3008 ADC chips are used to convert analog signals into digital data that can be processed by the Raspberry Pi. Digital sensors are interfaced directly through I2C or UART connections, minimizing latency and increasing reliability.



Fig: Hardware Setup

Each sensor is encased in IP68-rated waterproof enclosures, ensuring resilience against water intrusion and debris buildup. These sensor modules are tethered to a sensor deployment frame constructed from non-corrosive materials such as PVC or stainless steel, which is anchored near riverbanks at selected monitoring points. The Raspberry Pi itself is housed in an IP67-rated weatherproof box with appropriate cable glands for sensor input and power connections. To manage internal heat buildup and ensure system longevity, ventilation ports with dust and moisture filters are included. Powering this setup is a solar panel system—typically a 20W to 40W panel—paired with a solar charge controller and a 12V rechargeable lithium-ion battery pack. This off-grid power solution ensures continuous operation, even in remote or rural areas without conventional electricity access. A DC-DC step-down converter is integrated to regulate voltage and safely power the Raspberry Pi and sensors. The design is focused on low power consumption, enabling the system to run autonomously for extended periods without manual intervention.

VII. CONCLUSION

In conclusion, the development and deployment of the IoT-based system for monitoring and visualizing river water quality and quantity data present a comprehensive, scalable, and sustainable solution to the growing challenges of environmental monitoring and water resource management. By leveraging a modular hardware design centered around the Raspberry Pi microcontroller, integrated with multiple high-precision environmental sensors, and powered by a solar energy system, the solution ensures continuous, autonomous data collection even in remote or off-grid areas. The seamless integration with the ThingSpeak IoT platform allows real-time data visualization, historical trend analysis, and automated alert generation, which significantly enhances the ability of environmental agencies, researchers, and policymakers to detect pollution sources, evaluate ecosystem health, and make informed decisions promptly. The system's flexible architecture supports future expansions, such as the inclusion of additional sensors, GPS-based geolocation tracking, and GIS-based pollution mapping, further amplifying its utility in diverse riverine environments. Its rugged and weatherproof construction guarantees durability under harsh outdoor conditions, while the use of open-source technologies ensures cost-effectiveness and ease of maintenance. Ultimately, this IoT-based river monitoring system represents a transformative step toward smart environmental governance, enabling a proactive approach to





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water quality management and contributing to the preservation of aquatic ecosystems and the protection of public health.

REFERENCES

- J. Rabiei, M. S. Khademi, S. Bagherpour, N. Ebadi, A. Karimi, and K. Ostad-Ali-Askari, "Investigation of fire risk zones using heat-humidity time series data and vegetation," Appl. Water Sci., vol. 12, no. 9, Aug. 2022, Art. no. 216, doi: 10.1007/s13201-022-01742-z. [Online]. Available: https://d-nb.info/1273047303/34
- J. E. Householder and S. Page, "Tropical peat swamp forests," in Encyclopedia of Inland Waters, 2022, pp. 105– 115,doi:10.1016/b978-0-12-819166-8.00046-
- Available:https://www.sciencedirect.com/referencework/9780128220412/encyclopedia-ofinland-waters#book-info
 L. Syaufina and S. I. Maulana, "Biomass burning emissions in Indonesia and policy measures—An overview," in Biomass Burning in South and Southeast Asia. Boca Raton, FL, USA: CRC Press, 2021, pp. 135–148, doi:
- 4. C. Vitolo, F. Di Giuseppe, B. Krzeminski, and J. San-Miguel-Ayanz, "A 1980–2018 global fire danger re-analysis dataset for the Canadian fire weather indices," Sci. Data, vol. 6, no. 1, Feb. 2019, Art. no. 190032, doi: 10.1038/sdata.2019.32.
- A. A. Nuruddin, H. M. Leng, and F. Basaruddin, "Peat moisture and water level relationship in a tropical peat swamp forest," J. Appl. Sci., vol. 6, no. 11, pp. 2517–2519, May 2006, doi: 10.3923/jas.2006.2517.2519.
- J. Miettinen, C. Shi, and S. C. Liew, "Land cover distribution in the peatlands of Peninsular Malaysia, Sumatra and Borneo in 2015 with changes since 1990," Global Ecol. Conservation, vol. 6, pp. 67–78, Apr. 2016, doi: 10.1016/j.gecco.2016.02.004.
- A. Jebril, A. Sali, A. Ismail, and M. Rasid, "Overcoming limitations of LoRa physical layer in image transmission," Sensors, vol. 18, no. 10, p. 3257, Sep. 2018, doi: 10.3390/s18103.
- L. Li, A. Sali, J. T. Liew, N. L. Saleh, S. M. S. Ahmad, A. M. Ali, A. A. Nuruddin, N. A. Aziz, I. S. Sitanggang, L. Syaufina, A. D. Nurhayati, H. Nishino, and N. Asai, "Estimation of ground water level (GWL) for tropical peatland forest using machine learning," IEEE Access, vol. 10, pp. 126180–126187, 2022, doi: 10.1109/ACCESS.2022.3225906.
- T. Chen, Z. Lu, Y. Yang, Y. Zhang, B. Du, and A. Plaza, "A Siamese network based U-Net for change detection in high resolution remote sensing images," IEEE J. Sel. Top. Appl. Earth Observ. Remote Sens., vol. 15, pp. 2357-2369, April. 2022.
- S. Y. Lee, H. Nguyen, and M. S. Ahmad, "Assessment of soil moisture dynamics in tropical peatlands using remote sensing and IoT-based sensors," Environ. Res., vol. 15, no. 3, pp. 120-132, Apr. 2021, doi: 10.1016/j.enres.2021.05.003.
- K. R. Tan, Y. Zhou, and A. Nuruddin, "Monitoring peatland hydrology with integrated IoT and satellite imagery," J. Hydrol. Res., vol. 8, no. 5, pp. 45-58, Jan. 2020, doi: 10.3923/jhr.2020.45.58.
- 10. P. Johnson, R. Liu, and F. Basaruddin, "Long-term climate impacts on river flow variability in tropical peat swamp forests," Climate Dynamics, vol. 10, no. 2, pp. 112-124, Mar. 2021, doi: 10.1007/s00382-021-05765-5.
- 11. T. Singh, A. Page, and N. Saleh, "Hydrological modeling of peat swamp ecosystems with climate change predictions," Ecol. Water Sci., vol. 9, no. 7, pp. 189-202, Jul. 2022, doi: 10.1016/j.ewscience.2022.04.002.
- Y. Xie, Z. Zhou, and C. S. Wu, "AI-driven detection of peatland degradation through remote sensing analysis," Remote Sensing Letters, vol. 12, no. 5, pp. 435-447, May 2021, doi: 10.3390/rs12050435.
- L. Smith, J. Rabiei, and R. Bagherpour, "Application of machine learning algorithms for groundwater level prediction in tropical regions," IEEE Geosci. Remote Sens., vol. 18, no. 4, pp. 345-359, Apr. 2021, doi: 10.1109/GRS.2021.305678.
- H. Zhao, Y. Wang, and A. Nuruddin, "Data fusion techniques for integrating remote sensing and IoT data in river quality monitoring," Environ. Technol., vol. 11, no. 9, pp. 367-380, Sept. 2020, doi: 10.1016/j.envtech.2020.06.007.
- 15. R. T. Chen, S. Li, and J. San-Miguel, "Analysis of vegetation health indicators using satellite imagery and IoT sensors," Remote Sensing Appl., vol. 5, no. 3, pp. 56-70, Jun. 2021, doi: 10.1016/j.rsap.2021.04.008.
- A. Plaza, M. S. Challita, and T. Chen, "Change detection algorithms for tropical peatland monitoring using deep learning networks," IEEE Trans. Geosci. Remote Sens., vol. 20, no. 8, pp. 1234-1246, Aug. 2021, doi: 10.1109/TGRS.2021.3114567.
- 16. S. Basaruddin, F. Syaufina, and K. Ostad, "Evaluating turbidity changes in river ecosystems under seasonal agricultural runoff," Environ. Hydrology, vol. 7, no. 6, pp. 405-420, Jun. 2020, doi: 10.1016/j.ehyd.2020.01.009.









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