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Implementation of the Groundwater Live Observation for Water-Quality (GLOW) in Bojong District, Indonesia

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ABSTRACT

Many developing countries still predominantly rely on conventional monitoring of groundwater quality parameters. Emerging technologies have shown significant potential for advancing automated water quality monitoring in recent years. This study developed the Groundwater Live Observation for Water-quality (GLOW) system, which leverages Internet of Things (IoT) technologies combined with water quality sensors. In future applications, this remote sensing-based groundwater monitoring system holds strong potential for detecting pollutant intrusion in water bodies. The GLOW system was tested during two periods, namely from June 2023 to November 2023 and from January 2024 to March 2024, in Bojong District, Sukabumi Regency, Indonesia. The system employed Aqua TROLL 500 sensors capable of measuring water temperature, electrical conductivity (EC), pH, salinity, and total dissolved solids (TDS). The data generated by the GLOW system were transmitted to a website server and subsequently evaluated against laboratory-based data using statistical analyses. The Wilcoxon Signed-Rank Test was applied to assess differences between the two approaches. Most parameters showed no statistically significant differences ($p>0.05$), except for TDS and salinity ($p=0.02$). The Bland-Altman analysis confirmed good overall agreement between the two methods, with small mean differences for pH (0.19), EC (8.45 µS/cm), water temperature (-0.34°C), salinity (0.02 PSU), and TDS (0.01 ppm). Future research should expand monitoring by including nitrogen and phosphorus compounds.

HIGHLIGHTS

- Developed IoT-based sensors for continuous groundwater quality monitoring
- Findings support sustainable groundwater management and monitoring assessment
- Autonomous monitoring system validated using real field observations

1. INTRODUCTION

Groundwater is a widely utilized source of drinking water, with approximately 2.5 billion people globally relying on it (Grönwall and Danert, 2020). Consequently, groundwater management is considered one of the key strategies for addressing water scarcity (Carrard et al., 2019). In recent years, an alarming decline in groundwater quality has been reported in several Asian countries, particularly China, India, and Pakistan (Yin et al., 2020; Li et al., 2022, Ullah et al., 2022; Thakur et al., 2024). Groundwater contamination is commonly attributed to industrial pollution, domestic waste, agricultural runoff, and saltwater intrusion, and this widespread issue raises growing concerns as it poses significant health risks, contributes to environmental degradation, and exacerbates water scarcity. Providing early assessments of groundwater contamination and establishing strategic frameworks to address these issues are crucial first steps toward achieving resilient

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groundwater quality. Traditionally, groundwater quality monitoring has relied on field sampling and laboratory analysis, methods that have been well established and validated over decades, and whose results are widely accepted for regulatory and legislative purposes (Madrid and Zayas, 2007). However, this conventional monitoring approach is time-consuming, labor-intensive, and cost-inefficient (Abdulkadir et al., 2023; Jayaraman et al., 2024). Moreover, extensive and careful sample handling is required to prevent measurement errors and biases introduced by external factors such as exposure to sunlight or high air temperatures (Sani et al., 2023), which may cause deviations from the actual condition of the samples at the time of collection.

Fortunately, the limitations of conventional groundwater quality monitoring can be addressed through remote monitoring. By utilizing sensors to measure water-quality parameters directly in the field, there is no need to transport samples to a laboratory. This approach helps prevent exposure-related changes that could alter the chemical composition of groundwater. Sensors have been well developed to measure physicochemical parameters, such as pH, temperature, electrical conductivity (EC), and dissolved oxygen (DO). Further developments have broadened to even wider water quality parameters, such as total organic carbon (TOC), dissolved organic carbon (DOC), biological oxygen demand (BOD), chemical oxygen demand (COD), bacteria, agricultural pollutants, ions, and heavy metals (Park et al., 2020; Kumar et al., 2024). Besides single-parameter sensors, several configurable multi-parameter sensors are also available for long-term monitoring (Danielson, 2020). Nevertheless, the sensors must still be calibrated regularly to ensure that their accuracy is maintained. Another recent approach involves the use of Internet of Things (IoT) (Akrout et al., 2024), virtual sensing (Grisez et al., 2025), a cyber-physicochemical system (CPS) (Yoon et al., 2024), and optical techniques (Zainurin et al., 2022). As a result of ombining the sensors with the capacity of the current cloud system (hence the IoT services), groundwater monitoring is now capable of storing, transmitting, and analyzing real-time water quality data at almost real-time temporal scale. Such a platform is developed on IP-enabled devices and applications through wired (Ethernet) or wireless (Wi-Fi) interfaces (Wong and Kerkez, 2016).

One example of a monitoring system application was demonstrated in a study by Yoon et al. (2024), which utilized an IoT-integrated groundwater monitoring system to measure physicochemical parameters related to organic decomposition from livestock carcasses at a burial site. Four parameters were monitored: EC, chloride (Cl^-), nitrate nitrogen (NO_3-N), and ammonium nitrogen (NH_4-N). The monitoring system achieved high levels of accuracy and precision, ranging from 93.3% to 100.0% and 0.1% to 5.0%, respectively. EC was identified as the most reliable indicator among these parameters, as sensor readings differed by only 1.1 times compared with laboratory measurements. In contrast, the other parameters showed larger variations, with differences ranging from 1.6 to 2.5 times higher. On the other hand, real-time groundwater monitoring has not been widely implemented in Indonesia. Existing studies (Lubis et al., 2008; Hutabarat and Ilyas, 2017) are limited to single-parameter observations, such as groundwater table elevation or depth-temperature profiles. The studies conducted by Fakhrurroja et al. (2023) and Andayani et al. (2021) also assessed the feasibility of using sensors to measure groundwater quality parameters. However, both investigations were limited to laboratory-scale experiments, and to date, no field-based, real-time groundwater quality monitoring system has been implemented in Indonesia. The limited monitoring network restricts efforts to relate groundwater quality to spatial factors such as abstraction, land cover, and industrial pollution. A practical solution is installing multi-parameter monitoring systems, which allow real-time data collection and more accurate interpretations of groundwater characteristics, particularly in data-scarce regions.

Therefore, this study aims not only to develop but also to evaluate the application of the Groundwater Live Observation for the Water Quality (GLOW) system in Indonesia. The GLOW system was deployed in Bojong District, Sukabumi Regency, where a web-based platform continuously monitored groundwater quality parameters. Building on the success of previous studies (Yoon et al., 2024), which indicated that EC showed the closest agreement with field measurements among monitored parameters, this study focused on five other parameters: temperature, pH, EC, salinity, and total dissolved solids (TDS). These parameters were simultaneously measured in the laboratory through conventional sampling for comparison. Once the core parameters have been established, additional physicochemical parameters (Cl^-, NO_3-N, and NH_4-N) will be incorporated into the monitoring framework. Sensor-laboratory agreement is evaluated using uni-variate statistical metrics to validate the reliability of the GLOW system. Although no new sensor hardware is introduced, this study provides novel field-based evidence on the performance of real-time groundwater monitoring in data-scarce regions such as Indonesia. In future applications, the GLOW system may also be used to detect potential pollutant intrusion into water bodies.

2. METHODOLOGY

2.1 Study location

The monitoring well, equipped with the aforementioned sensors, is located in the Sukabumi Regency, near the south coast of West Java Province, Indonesia. Figure 1 shows the Sukabumi Regency's relative position and the exact position. Geologically, the northern part of the Sukabumi area is dominated by alluvium deposits and young volcanic deposits of the Quaternary Age. Considering their alluvial nature, the geologically young and unconsolidated soils should support productive aquifer potential in these areas. On the other hand, a high-water table might also leave the area prone to flooding without proper stormwater management. As the Sukabumi Regency is situated in a tectonically active region between the Indo-Australian and Eurasian plates, fractured tertiary rocks and volcanic structures may lead to amplified risk of seismic potential. The groundwater hydraulic head especially that from confined aquifers, is harder to qualitatively predict, as the fragility to seismic activities could coerce the aquifers to karsting and perching exposure.

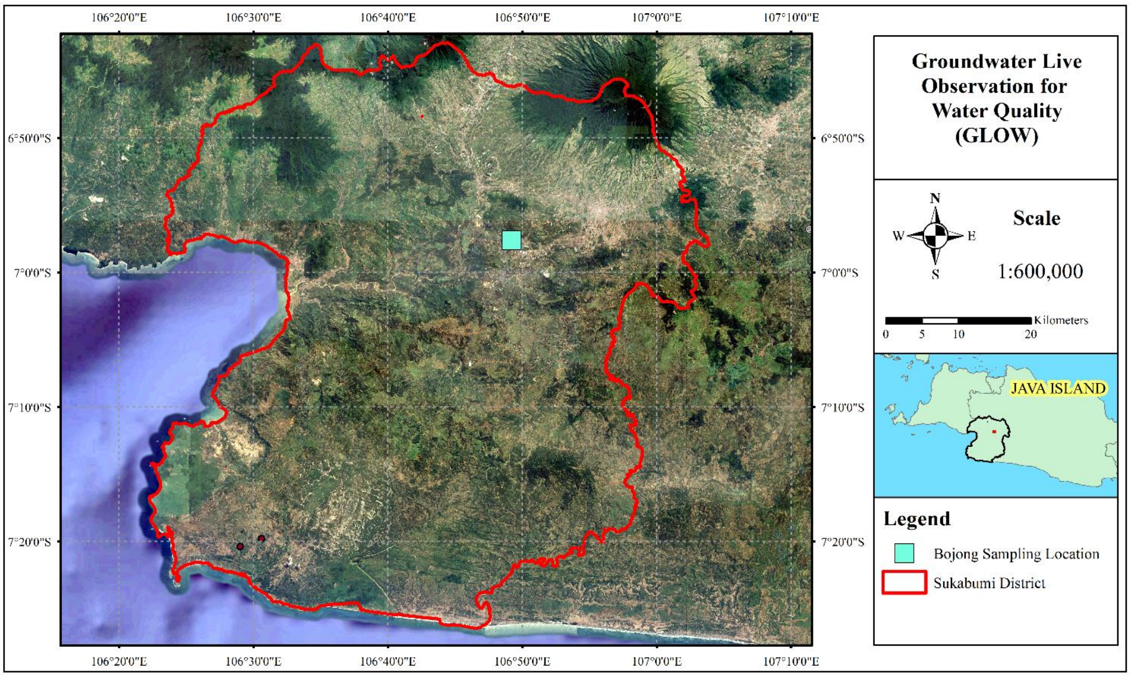

Figure 1. The monitoring well in Bojong District, Sukabumi Regency, Indonesia

The geographical coordinates of the Bojong monitoring well are 106.82°E and 6.96°S. The planned design of the well is shown in Figure 2(a), where the borehole was drilled to a depth of 120 m. As illustrated, two types of PVC casing were installed. From the surface to a depth of 6 m, a non-perforated PVC pipe was used and reinforced with cement grouting. From 6 m down to 120 m, a perforated PVC pipe was installed to allow groundwater to enter the well. The perforated section was surrounded by gravel, sized 0.50-1.00 cm, to ensure the pipe remained stable and properly positioned within the borehole. During the drilling process, geophysical logging was conducted to determine the resistivity profile and classify subsurface lithology down to 120 m. Based on resistivity values, the subsurface materials can be categorized as tuff (1-10 Ω.m), tuffaceous sand (10-50 Ω.m), and gravel (50-100 Ω.m) (Palacky, 1998; Telford et al., 1990). The resulting lithological classification is presented in Figure 2(b), which shows that the subsurface is predominantly composed of tuff layers. Geo-electric measurements further indicate that the monitoring well intersects a shallow aquifer between depths of 3 and 30 m.

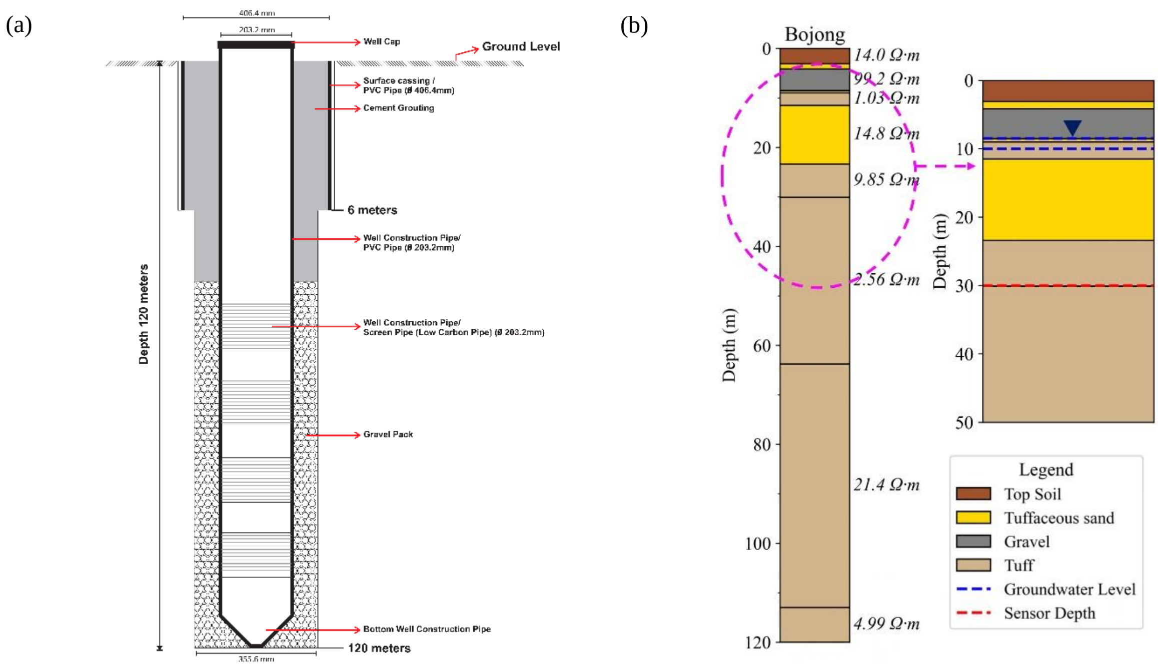

Figure 2. (a) Well construction design plan and (b) the soil stratigraphy of the Bojong Site

2.2 The GLOW system

The Aqua TROLL 500 sensor was selected for its proven effectiveness in monitoring water quality parameters (Acrohm, 2020; Snow et al., 2020). It comes in two main sondes, vented and non-pressurized, whose specifications for measuring water quality parameters are presented in Table 1. Both sondes were installed at a depth of 30 meters, situated in the tuff layer in the well. The soil layer is characterized by soft, porous volcanic rock (Asniar et al., 2019), facilitating groundwater flow around the sondes. Nevertheless, the tuff layer is less permeable than the gravel layer (Siegesmund et al., 2023), resulting in more stable concentrations of water-quality parameters within the well compared to those in the gravel layer. This consideration formed the primary basis for selecting a depth of 30 m as the installation level for both sondes. A gateway panel was also installed with a protective box, which safeguards the internal components from external elements such as extreme weather conditions and insects. A weather sensor is also integrated into the GLOW system to monitor ambient air temperature. The system is programmed to record all parameters at 10-minute intervals. It has been maintained and calibrated monthly from June 2023 to March 2024.

Table 1. The Aqua Troll 500 sensor specifications (Acrohm, 2020)

Parameter	Accuracy	Range	Methodology
EC	±0.5% of reading plus 1 µS/cm*	0 to 350,000 µS/cm	Std. Methods 2510, EPA 120.1
TDS	-	0 to 350 ppm	-
Salinity	-	0 to 350 PSU	Std. Methods 2520A
pH	±0.1 pH units	0 to 14 pH units	Std. Methods 4500-H+, EPA 150.2
Temperature	±0.1ºC	-5 to 50ºC	EPA 170.1

Within the box of the gateway panel, several components are installed to enable data visualization, sensor calibration, and automated data uploading to the website server. During the initial testing period, the system was powered by the state electricity grid (220V AC). This power was stored in an uninterruptible power supply (UPS) and then converted to 12V DC to meet the system's operational requirements. A supporting 18 V DC solar panel was integrated, with its output regulated to 12 V DC via a 0.50. A solar charge controller (SCC). Unstable power supply may cause sudden spikes in the sensor readings. Therefore, all sensor outputs must be verified manually before being accepted as valid final data. Wi-Fi connectivity is established to facilitate real-time data transmission. As a contingency measure, flash drives are employed for local data storage in the event of transmission failures. A complete schematic diagram of the GLOW system is presented in Figure 3, while the installed system is shown in Figure 4.

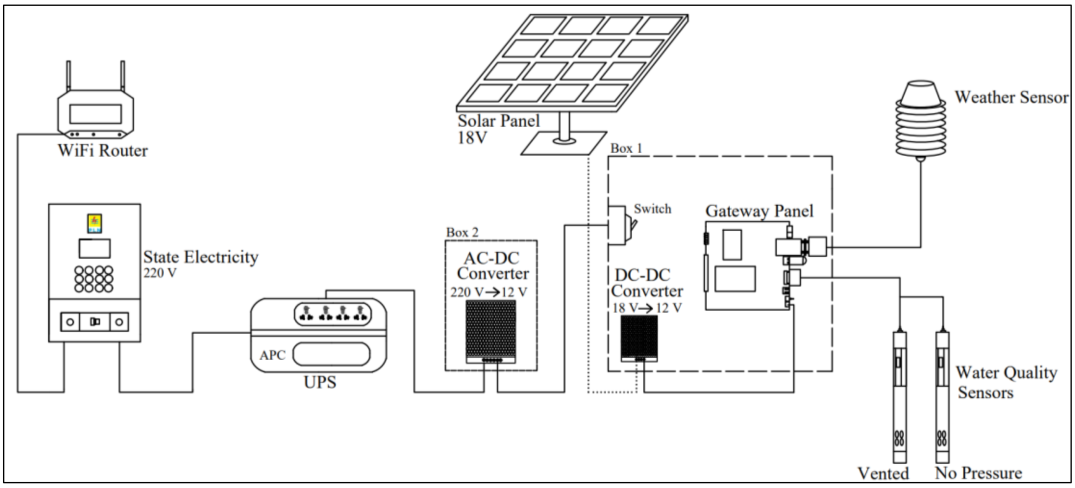

Figure 3. The schematic diagram of the GLOW system

Figure 4. The installed GLOW system at the Bojong Site

2.3 Conventional monitoring of water quality parameters

In conventional monitoring, water samples are assessed using in-situ tools based on established physical principles (YSI Inc, 2021). The groundwater level within the well fluctuated between depths of 7 and 10 m; therefore, water sampling was conducted within this interval. As shown in Figure 2(b), the groundwater is hosted within the tuff and tuffaceous sand layers. Although the water sampling depth and the sensor installation depth differ, the surrounding lithological units at these elevations are comparable. This approach was adopted to minimize variations in groundwater quality concentrations, as discussed in the previous section. pH is measured using an ion-selective electrode (ISE), with an accuracy of ±0.2. Water temperature is monitored using a thermistor, typically covering a range from -5°C to 70°C, with an accuracy of ±0.2°C. EC is determined via a conductivity electrode sensor (conductometry), operating within a range of 0 to 200 µS/cm and with an accuracy of ±0.5%. Salinity and TDS are not measured directly but are calculated from EC values using the Practical Salinity Scale 1978 (PSS-78) and an empirical conversion factor, respectively.

2.4 Statistical methods

This study employed three methods to assess the performance of the GLOW system: normality tests, non-parametric statistical methods, and Bland-Altman plots. The normality test was used to evaluate the sensor's data distribution. One commonly used normality test is the Kolmogorov-Smirnov test, which is suitable for large sample sizes ($n>5,000$) (Ghasemi and Zahediasl, 2012). The characteristics of the Kolmogorov-Smirnov statistical test are well suited to this study, as the dataset analyzed can comprise tens of thousands of observations for a single parameter. If the p-value generated by the Kolmogorov-Smirnov test is less than 0.05, the data are considered not normally distributed.

When data are not normally distributed, non-parametric statistical methods are more appropriate for evaluating accuracy (Holmes, 2020). One such method is the Wilcoxon Signed-Rank Test, which assesses whether the differences between paired observations are statistically significant. The Wilcoxon Signed-Rank Test is specifically designed for paired observations collected at corresponding time points. Moreover, since it is based on median differences rather than means, this method is more robust to outliers and non-normal data distributions. Like the normality test, the Wilcoxon Signed-Rank Test evaluates its difference using p-values. If the p-value in the Wilcoxon Signed-Rank Test is greater than 0.05, the parameter does not differ significantly. Since this study aims to evaluate the performance of the GLOW system, the laboratory-based measurements are considered the reference or "true" values.

Finally, Bland-Altman plots were employed to visually examine the agreement between the sensor-based and laboratory-based data at corresponding time points. These plots help identify the number of data points within an acceptable range, commonly defined as within 95% of the reference range (Mansournia et al., 2021). This analysis provides insight into the extent to which the sensor-based data either underestimates or overestimates the laboratory-based data. This method is highly relevant for instrumentation and sensor studies, as sensors may exhibit small but consistent differences that can be statistically significant yet remain acceptable from an operational perspective.

3. RESULTS

3.1 The GLOW's reading

The 10-minute interval sensor data were aggregated into daily averages before being plotted with the laboratory-based data. Sensor readings and laboratory analyses are divided into two periods. The first period, covering both sites, spans from 27 June 2023 to 14 November 2023, as presented in Figure 5. The second period extends from 29 January 2024 to 15 March 2024, as illustrated in Figure 6. As previously mentioned, this separation was necessitated by a maintenance interval caused by power fluctuations in late November 2023. Another distinguishing factor between the two periods is that the GLOW system operated solely on the state electricity grid during the first period. In contrast, it was powered by combining a solar panel system and the state electricity grid in the second period.

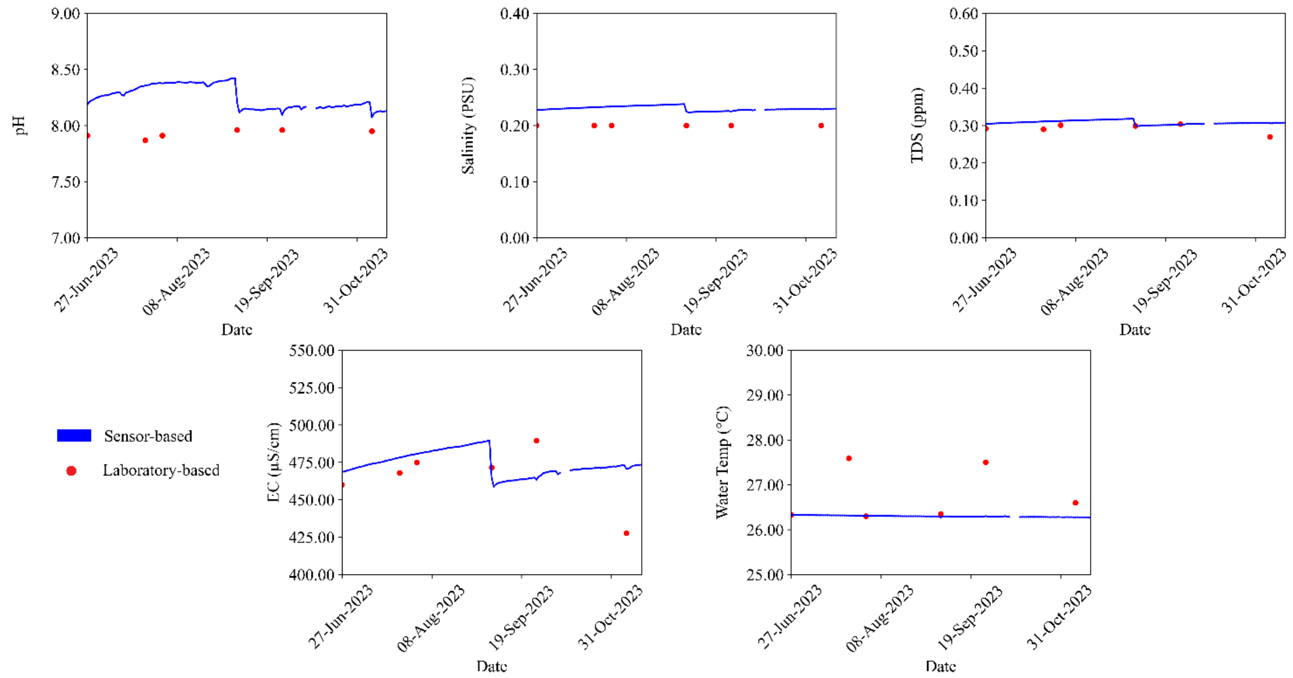

Figure 5. Time series of water quality parameters during the first monitoring period

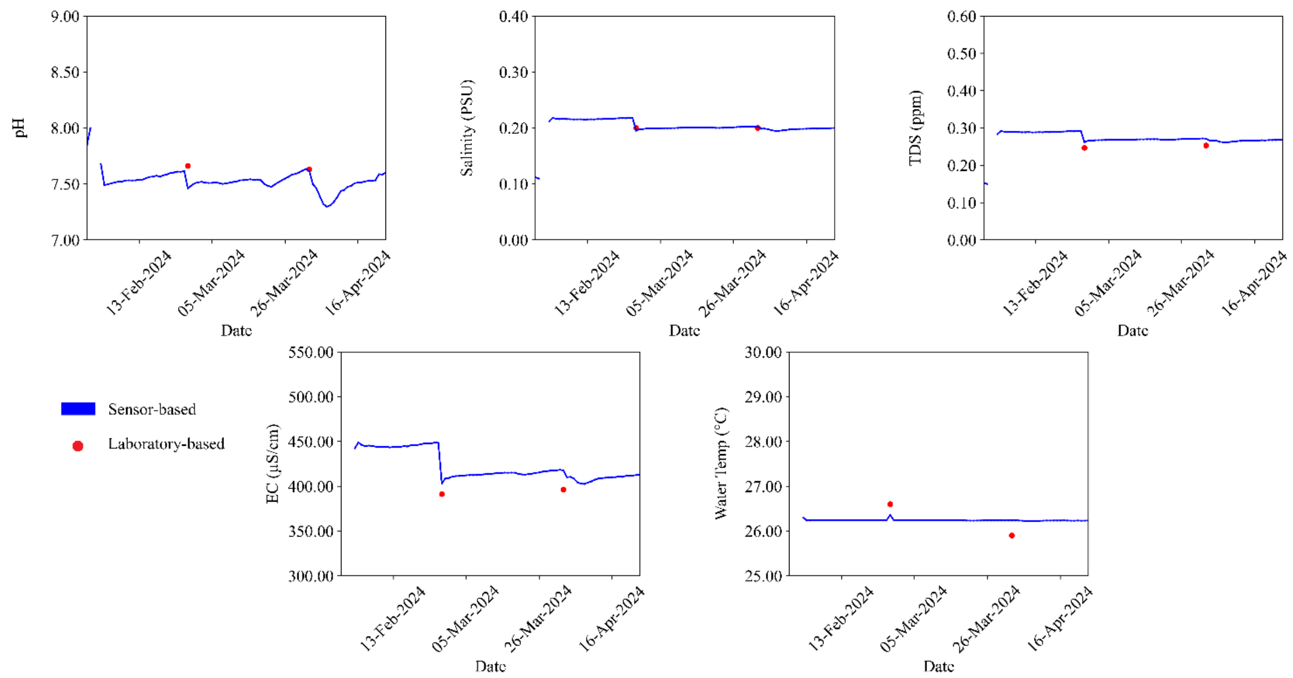

Figure 6. Time series of water quality parameters during the second monitoring period

During the first period, a three-day data loss occurred in early October 2023. The data loss could not be recovered due to a complete shutdown of the GLOW system. As shown in Figure 5, the sensor readings for the five water quality parameters appear to be sufficiently accurate, although pH, salinity, and EC tend to be slightly overestimated. This discrepancy may also be attributed to the fact that the water samples were taken from a shallower depth, potentially resulting in higher laboratory-based values than sensor readings. Notably, the TDS parameter exhibited the most accurate agreement between the two data sources. In the second period, a one-day data loss still occurred at the beginning, as shown in Figure 6. Although data loss persisted, the duration of sensor data unavailability was significantly reduced.

The percentage of system uptime during both monitoring periods was quantified by calculating the difference between the total monitoring duration and the system downtime, divided by the total monitoring period. During the first monitoring period, the system experienced three days of downtime over 140 days of observation, while during the second monitoring period, one day of downtime occurred over 46 days of monitoring. Based on these values, the system uptime for the first and second monitoring periods was 97.86% and 97.83%, respectively. Nevertheless, the GLOW system can still be further improved to ensure a more stable and continuous power supply.

Based on the visual inspection of the time-series results from both monitoring periods, the sensor-generated data can be considered sufficiently reliable. One or two parameters exhibited noticeable fluctuations, which posed challenges for data validation; however, highly fluctuating readings were carefully filtered prior to analysis to ensure data quality. Several field improvements were implemented, including the installation of a solar panel to supplement electricity demand and the use of an uninterruptible power supply (UPS) to stabilize grid-supplied power. Despite these efforts, power instability was not fully resolved, as the addition of only one solar panel during the second monitoring period was insufficient to meet the system's energy requirements. Another limitation of this study relates to its location in relatively underdeveloped areas with limited internet connectivity, which occasionally disrupted data transmission to the web server. To mitigate this issue, flash drives were employed for local data storage, as described in the previous section.

3.2 Outcomes of statistical analysis

A Kolmogorov-Smirnov test for normality was applied to the sensor-based data with a temporal resolution of 10 minutes, and the results are presented in Table 2. Since all water quality parameters have a p-value of 0, the parameters are stated as not normally distributed. These findings indicate the Wilcoxon Signed-Rank Test is a suitable method for subsequent analysis. The results of the Wilcoxson Signed-Rank Test are shown in Table 3. Most parameters show no significant difference between the GLOW system and the laboratory-based data. The parameters with significant differences are TDS and salinity. However, one thing that might be considered is that our method's precision in measuring the salinity is relatively low. The salinity value can only be detected with one significant number, either 0.20 or 0.30. This condition is undoubtedly affecting the Wilcoxson Signed-Rank Test results.

Table 2. The Kolmogorov-Smirnov test results

Parameter	KS Statistic	p-value
pH	0.23	0
Salinity	0.19	0
TDS	0.46	0
EC	0.20	0
Water Temp.	0.47	0

Table 3. The Wilcoxson Signed-Rank test results

Parameter	Number of data used	p-value	Remarks
EC	8	0.25	There is no significant difference
pH	8	0.08	
Water Temp.	8	0.20	
TDS	8	0.02	There is a significant difference
Salinity	8	0.02	

Next, the differences between the two types of data were visualized using the Bland-Altman Plot, as presented in Figure 7. The outcomes of these plots are consistent with those obtained from the Wilcoxon Signed-Rank Test. In the study location, as shown in Figure 7, the pH, EC, water temperature, salinity, and TDS parameters exhibited mean differences of 0.19, 8.45 µS/cm, -0.34°C, 0.02 PSU, and 0.01 ppm, respectively. Despite being identified as having significant differences, the Bland-Altman plots of salinity and TDS parameters are still acceptable. Furthermore, all the sensor-based data remained within a safe reference range. These small differences suggest that, despite some inconsistencies, the GLOW system remains reliable for real-time groundwater quality monitoring purposes.

Despite the operational challenges encountered in the field, the sensor-based data demonstrated sufficient accuracy in providing reliable real-time measurements of groundwater quality parameters. The results of the Wilcoxon Signed-Rank Test for all parameters were statistically promising, except TDS and salinity. Furthermore, the Bland-Altman plots provided a complementary assessment, showing that all paired sensor and laboratory measurements for each water quality parameter fell within the 95% limits of agreement, indicating acceptable agreement between the two methods. In addition, this study was limited to eight water sampling events conducted over the eight-month system testing period. With such a small sample size, hypothesis-testing methods may place excessive emphasis on statistical significance and may not fully reflect practical sensor performance. Consequently, agreement-based approaches, such as the Bland-Altman limits of agreement, provide a more appropriate framework for evaluating sensor reliability. To strengthen future validations, more frequent or extensive laboratory measurements are recommended to better support the assessment of sensor-based data.

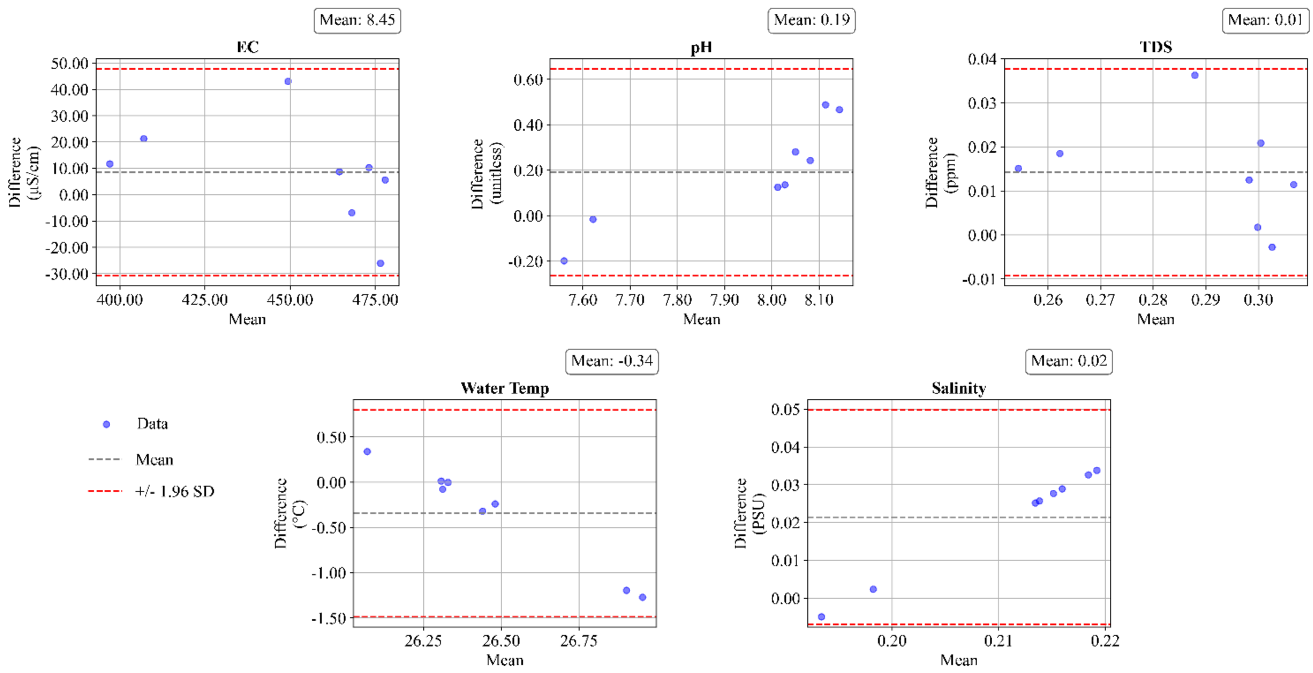

Figure 7. Bland-Altman Plots for each water quality parameter

4. DISCUSSION

The addition of one solar panel during the second monitoring period did not result in a significant improvement in the stability of the electricity supply. During this period, the system employed a 0.5 A SCC, for which the calculated power generation was only approximately 30 Wh per day. In contrast, the GLOW system requires 54.72 Wh per day to operate reliably. In evaluating the net energy balance between power consumption and power generation, state electricity was excluded from the analysis because frequent power outages rendered it unreliable. As the SCC capacity remained at 0.5 A, the addition of an extra solar panel did not increase the effective power output. Instead, increasing the SCC current rating represents a more viable solution. Therefore, an energy budget analysis comparing power consumption and power generation was conducted, as presented in Table 4. In this analysis, the solar panel was assumed to charge the battery for an effective duration of 5 hours per day. Power generation was estimated for SCC capacities of 1.0 A, 1.5 A, and 2.0 A. The results indicate that the system's energy demand can be met when an SCC with a capacity of at least 1.0 A is employed. However, as a precautionary measure, an SCC capacity of 1.5-2.0 A is recommended to account for external factors such as prolonged cloudy or rainy conditions. This configuration is expected to provide a stable 12 V DC output to sustain continuous system operation.

The results demonstrate that real-time groundwater quality monitoring using IoT-based systems is technically feasible and potentially scalable to other developing regions. However, a careful assessment of site-specific conditions is essential to ensure that the data produced is sufficiently reliable for decision-making. Collaborations with local stakeholders could support such systems' long-term sustainability and scalability. This study provides a foundational case for developing a nationwide groundwater monitoring network, which could inform both short-term groundwater pollution alerts and long-term aquifer management strategies. Future efforts should focus on developing sensors capable of measuring additional chemical parameters, particularly nitrogen and phosphorus compounds. These parameters serve as direct indicators of water quality degradation, as their concentrations are strictly regulated to ensure the safety of human consumption. Including such indicators would significantly enhance the comprehensiveness of the monitoring system and support early detection of nutrient pollution, particularly in areas influenced by agricultural runoff or domestic wastewater discharge.

Table 4. Energy budget comparing power consumption and power generation

Parameter	Power consumption	Power generation			
		SCC with capacity			
		0.5 A	1.0 A	1.5 A	2.0 A
Voltage (V)	12				
Electricity Current (I) [A]	0.19	0.50	1.00	1.50	2.00
Power (P) [W]	2.28	6.00	12.00	18.00	24.00
Time [hour]	24.00	5.00			
Energy [Wh]	54.72	30.00	60.00	90.00	120.00
Net energy [Wh]		-24.72	5.28	35.28	65.28
Suffice?		Not Sufficient	Sufficient	Sufficient	Sufficient

One of the parameters that can be directly compared with the previous study by Yoon et al. (2024) is EC. As mentioned earlier, sensor-based EC values in the prior study were 1.1 times higher than those obtained from laboratory measurements, with a reported correlation coefficient of 0.3834. However, this result alone does not provide sufficient evidence regarding whether the recorded values fall within a statistically acceptable confidence interval. In the present study, as shown in Figure 7, all paired comparisons between sensor- and laboratory-based EC measurements fall within the 95% confidence interval, with an average error of only 8.45 µS/cm. These finding underscores progress in the implementation of groundwater monitoring systems. Furthermore, other parameters showed a similar trend, with consistently small mean error values.

5. CONCLUSION

The groundwater live observation for water-quality (GLOW) system was successfully implemented in the Bojong study area to continuously monitor five groundwater quality parameters: pH, EC, temperature, salinity, and TDS. Comparative analysis between sensor-based and laboratory-based measurements demonstrated acceptable agreement, with most parameters showing no statistically significant differences based on the Wilcoxon Signed-Rank Test. The Bland-Altman plots further confirmed the small magnitude of discrepancies, with mean differences of 0.19 for pH, 8.45 µS/cm for EC, -0.34°C for temperature, 0.02 PSU for salinity, and 0.01 ppm for TDS, underscoring the reliability of the system in capturing key physicochemical dynamics of groundwater. Nonetheless, data loss persisted even after solar panel installation, indicating insufficient power availability and the need for a more robust solution, such as increasing the SCC capacity to 1.5-2.0 A. Despite this limitation, the GLOW system proved to be an effective tool for real-time groundwater monitoring and holds promising potential for early detection and management of water quality degradation in Indonesia.

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AUTHOR CONTRIBUTIONS

Conceptualization, D.Y. and Y.C.S.; Methodology, F.F.; Validation, A.W. and A.T.; Formal Analysis, S.K.H. and S.S.; Investigation, N.G.S.; Resources, S.K.C.; Writing-

Original Draft Preparation, S.K.C.; Writing-Review and Editing, S.R.R.; Visualization, S.R.R.; Supervision, O.W.T.; Funding Acquisition, NC Environment Technology.

DECLARATION OF CONFLICT OF INTEREST

The authors declare no conflict of interest.

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