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A Low-Cost Lidar Based IoT System for Real-Time Remote Groundwater Level Monitoring: Design, Validation and Field Deployment

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ABSTRACT

Groundwater level monitoring is essential for sustainable water management, yet many developing regions lack affordable real-time infrastructure. This study presents the design, construction, and field validation of a low-cost, non-contact groundwater monitoring device integrating a Lidar-Lite v3HP time-of-flight sensor, an Arduino Uno microcontroller, and an ESP8266 Wi-Fi module for telemetry to the ThingSpeak IoT platform. The implemented device was powered by a 20,000mAH, 5V power bank and deployed on two artesian wells in Oghara, Delta State, Nigeria, the prototype was validated against manual tape measurements at depths of 167–739 cm. A linear correction factor derived from regression analysis mitigated systematic bias. Results showed near-perfect correlation (r = 0.99995) between Lidar and tape measurements, with the correction factor reducing root mean square error (RMSE) from 10.28 cm and 13.91 cm to 3.91 cm and 5.36 cm for Wells 1 and 2, respectively. Bland–Altman analysis confirmed a ten and three-fold decrease in bias respectively, while the coefficient of variation remained below 1.21%. With an average upload latency of thirty-three seconds, the system enables sub-minute monitoring, offering a robust, economically viable solution for expanding groundwater networks in resource-constrained regions.

INTRODUCTION

Groundwater represents over 95% of the planet's fresh liquid water and serves as the primary drinking source for approximately 85% of urban and 75% of rural populations in Nigeria (Cobbing et al., 2021; Kalu, 2018). Effective resource management depends on accurate, high-frequency monitoring of water table fluctuations, which provides essential data for estimating recharge rates, tracking contaminant migration, and assessing climate-induced variability (Healy & Cook, 2002; Masood et al., 2022; Taylor & Alley, 2001). Despite its hydrological significance, groundwater observation in many developing nations remains inadequate, characterized by labour-intensive manual measurements, manual retrieval of measurements, centralized data repositories with limited local accessibility, and reliance on contact-based sensors that are susceptible to corrosion, biofouling, and long-term drift (Boon et al., 2012; Calderwood et al., 2020; Nielsen & Nielsen, 2007).

The emergence of non-contact sensing methods namely ultrasonic, radar, and laser-based (Lidar) techniques, has created new opportunities for autonomous, high-resolution water level measurement (Wu et al., 2023). Among these, Lidar offers distinct advantages in rapid measurement cycles, reduced sensitivity to meteorological variability, and high accuracy across extended ranges (Benjamin & Kaplan, 2017; Paul et al., 2020). In the past, the deployment of Lidar in hydrometry was hampered by the inherently low reflectivity of water surfaces. At normal incidence, only approximately 2% of incident near-infrared laser power is reflected, with the remainder refracted into the water column, necessitating expensive high-power transmitters and ultra-sensitive detectors (Born & Wolf, 2019; Paul et al., 2020). Advances in sensing technology, including single-photon avalanche diodes and enhanced digital processing techniques have enabled compact, Lidar modules to register weak returns (Sony, 2021), justifying previous and later efforts in extending the technique to groundwater monitoring applications (Dementria et al., 2023; Paul et al., 2020; Tamari & Guerrero-Meza, 2016). Simultaneously, the proliferation of open-source Internet of Things (IoT) platforms such as ThingSpeak has dramatically lowered the cost barrier for real-time data telemetry, visualization, and cloud storage (Calderwood et al., 2020; Kondapuram et al., 2024). These technologies facilitate the transition from in-person manual monitoring to continuous, remotely accessible observation networks. Yet developing countries continue to rely predominantly on imported commercial dataloggers, and indigenous, context-appropriate monitoring solutions remain scarce. In Nigeria, the national groundwater monitoring programme operated by the Nigerian Hydrological Service Agency typically records 12-hourly measurements, a temporal resolution insufficient to capture short-term hydrological transients or to generate the high-density datasets required by contemporary machine learning and deep learning forecasting models (Ali et al., 2024; Igwebuike et al., 2025; Kalu, 2018).

This study addresses these interrelated challenges by designing, constructing, and rigorously validating a low-cost, Lidar-based real-time remote groundwater monitoring device. By integrating a Garmin Lidar-Lite v3HP time-of-flight sensor with an Arduino Uno microcontroller and an ESP8266 Wi-Fi module, the prototype achieves non-contact measurement with automatic cloud-based telemetry. The specific objectives were to: (i) establish reliable hardware and software interfaces between the Lidar sensor, microcontroller, and IoT platform; (ii) implement real-time Wi-Fi-based data transmission to ThingSpeak; and (iii) quantify the accuracy and reliability of the device through comprehensive statistical comparison with manual tape measurements obtained under field conditions.

MATERIALS AND METHODS

Hardware Architecture

The monitoring system comprises an Arduino Uno Rev 3 microcontroller (ATmega328P, 16 MHz), a Garmin Lidar-Lite v3HP time-of-flight sensor, an ESP8266 Wi-Fi module mounted on an ESP-01 adapter, and a 16 × 2 liquid crystal display (LCD) for local visual feedback. The Lidar-Lite v3HP operates at a wavelength of 905 nm, with a nominal range of 1–40 m, 1 cm resolution, and ±2.5 cm accuracy for distances ≥2 m (Garmin, 2018). Communication with the Arduino occurs via the Inter-Integrated Circuit (I^2C) protocol using the SDA (A4) and SCL (A5) pins. A 1000 µF electrolytic capacitor was placed across the sensor's power and ground rails to suppress current-induced voltage fluctuations during laser pulsing.

The ESP8266 module serves as a dedicated Wi-Fi modem, receiving formatted data via Universal Asynchronous Receiver-Transmitter (UART) serial communication (pins 11 and 12 on the Arduino) and transmitting HTTP GET requests to the ThingSpeak cloud platform. The ESP-01 adapter regulates the Arduino's 5 V supply to the 3.3 V required by the ESP8266 and ensures stable current delivery during radio transmission. A 10 kΩ potentiometer connected to the LCD V0 pin provides contrast adjustment. The complete system was assembled on a breadboard for prototyping and subsequently transferred to a veroboard housed in a protective enclosure.

Software and Telemetry

Firmware was developed in the Arduino Integrated Development Environment (IDE) using C/C++. The control algorithm initializes the I^2C bus, configures the Lidar-Lite to balanced acquisition mode, and establishes a Wi-Fi station connection by issuing AT commands to the ESP8266. Upon power-up, the system requires approximately 33 seconds to initialize and output its first reading. Each loop iteration triggers a distance measurement, applies a calibration correction, updates the LCD, and uploads both raw and corrected values to separate fields of a public ThingSpeak channel via the platform's write Application Programming Interface (API) key. A mandatory 15-second inter-upload delay was implemented to comply with the free-tier rate limit (Viegas et al., 2021).

Calibration and Field Deployment

Field validation revealed an offset between raw Lidar readings and manual tape measurements. Calibration was performed in two stages. First, a zero-point offset (*a*) was determined by mounting the sensor at a fixed height above the well and computing the mean difference between the Lidar output and the reference tape measurement. Second, a span linearity check was conducted across multiple groundwater levels achieved through controlled evacuation and natural fluctuation. The span linearity check was carried out to ascertain if the offset varied linearly with increased measured distance. It was observed that the offset increased slightly with distance measured. To obtain a constant offset bias to be applied in the equation for the correction factor, linear regression of raw Lidar values against tape measurements was executed in Excel and a slope and intercept was extracted from the regression relation given by Equation (1) as:

$$y = 1.01x - 12.40 \qquad (1)$$

Where the slope and intercept are 1.01 and 12.40 respectively.

The corrected Lidar distance was computed as:

$$R_{corrected} = \frac{(R_{raw} - a)}{b} \qquad (2)$$

where R_{raw}, is the uncorrected measurement, a is the offset bias (represented by the intercept in equation 1)

and b is a scaling factor represented by the reciprocal slope (Christakis et al., 2024).
The prototype was deployed at two hand-dug artesian wells in Oghara, Delta State, Nigeria. Manual measurements were obtained using a graduated steel tape lowered to the water surface. Time-stamped Lidar readings from the constructed device were recorded at depths spanning 167.4 –583.2 cm for Well 1 and 193.6 – 739.2 cm for Well 2.

Statistical Analysis
Validation employed Pearson's correlation coefficient (r) to assess linear relation, root mean square error (RMSE) to quantify average deviation, and Bland–Altman analysis to evaluate systematic bias and 95% limits of agreement (Altman & Bland, 1983; Giavarina, 2015). The coefficient of variation (CV) was computed as the percentage ratio of standard deviation to mean to assess measurement precision.

RESULTS AND DISCUSSION

System Performance and Telemetry
The device successfully transmitted groundwater level data to the ThingSpeak platform with an average upload latency of 33 seconds and an approximate success rate of 75%, contingent on local network stability. The upload rate was constrained by the free-tier ThingSpeak account limitation (≥ 15 seconds) rather than sensor acquisition time. These characteristics enable sub-minute monitoring frequencies, representing a substantial improvement over the 12-hourly intervals typical of existing national networks (Kalu, 2018). Real-time visualization of raw and corrected data streams was accessible remotely via the ThingSpeak dashboard, confirming the system's suitability for unattended telemetry.

Measurement Accuracy
Table 1 summarizes descriptive statistics for representative measurement depths. Both wells where the device was deployed were hand-dug artesian, unconfined aquifer having built up diameter of 80 cm and 82 cm and depth of about 10 m and 12 m respectively. The well lids were left open while readings were being taken. For Well 1 at a tape-measured depth of 481 cm, raw Lidar readings averaged 476 cm (SD = 2.46 cm, RMSE = 5.98 cm), whereas corrected readings averaged 483.16 cm (SD = 2.44 cm, RMSE = 3.34 cm). Thirty(30) Lidar reading were used to compute the mean Lidar value displayed in Table 1. At 583.2 cm, the RMSE decreased from 8.87 cm to 4.54 cm. For Well 2 at 234.1 cm, the raw RMSE of 12.25 cm was reduced to 2.94 cm post-correction; at 739.2 cm, the RMSE improved from 11.79 cm to 7.04 cm. *Note.* SD = standard deviation; RMSE = root mean square error.

Table 1: Summary of Some Lidar Measurement Accuracy Before and After Correction

Well	Tape depth (cm)	Raw mean (cm)	Raw SD (cm)	Raw RMSE (cm)	Corrected mean (cm)	Corrected SD (cm)	Corrected RMSE (cm)
1	481.00	476.00	2.46	5.98	483.16	2.44	3.34
1	583.20	576.00	4.57	8.87	582.18	4.52	4.54
2	234.10	222.00	2.28	12.25	232.19	2.25	2.94
2	739.20	727.46	4.00	11.79	732.60	3.96	7.04

Correlation analysis revealed near-perfect linear relationships between Lidar and tape measurements for both wells, with $r = 0.99995$ before and after correction. Critically, the regression intercept decreased from 13.39 cm and 12.87 cm to 0.82 cm and 2.33 cm for Wells 1 and 2, respectively, indicating that the correction factor effectively reduced the systematic offset while preserving the strong linear response.

Bland–Altman Agreement
Bland–Altman analysis was employed to examine the limits of agreement between methods. For Well 1, the mean bias was 9.5 cm for raw measurements, with 95% limits of agreement ranging from 4.55 cm to 14.45 cm. After correction, the bias fell to 0.96 cm and the limits narrowed to −2.40 cm and 4.32 cm. For Well 2, raw measurements exhibited a bias of 13.50 cm (limits: 10.19 cm to 16.81 cm), which decreased to 4.73 cm (limits: 2.49 cm to 6.98 cm) post-correction. The reduction in bias and the contraction of agreement limits for measurements from both wells confirm that the calibration procedure substantially enhanced both accuracy and precision.

Precision and Error Sources
The coefficient of variation for Well 1 improved marginally from 1.21% (raw) to 1.15% (corrected), while Well 2 improved from 0.56% to 0.54%. The consistently low CV values indicate high repeatability. The persistence of a small residual bias post-correction suggests that error sources are predominantly systematic (Jimenez-Olmedo *et al*, 2024). Probable contributors include: (i) the complex reflectivity dynamics of the water surface, where specular reflection dominates under calm conditions but surface rugosity induces diffuse scattering; (ii) atmospheric refractive index variations within the well column due to temperature and humidity gradients; and (iii) discrepancies between the optical

properties of the factory calibration target and the actual field water surface (Behzadian et al., 2025; Ruttner et al., 2025).

Continuous monitoring of individual measurement sessions further revealed that Lidar readings converged toward the tape measurement after several successive samples, consistent with the observations of Dementria et al. (2023). This convergence suggests that the sensor's internal noise-reduction algorithm—which accumulates and averages multiple pulse returns—requires a brief warm-up period to stabilize above the detection threshold. Incorporating this behavior into the calibration protocol by discarding initial transient readings or applying a dynamic moving average could further reduce residual error.

Contextualization with Existing Literature

The findings align with and extend recent studies on low-cost Lidar hydrometry. Dementria et al. (2023) reported a convergence phenomenon in which initial Lidar readings underestimated depth but stabilized after successive measurements; the present study confirms this behavior and demonstrates that a regression-derived correction factor can accelerate convergence and reduce residual error. Paul et al. (2020) evaluated near-infrared Lidar for river stage monitoring and noted increased accuracy at shorter ranges and rougher surfaces; the current findings corroborate the range-dependent bias but show that post-correction accuracy remains robust at groundwater monitoring distances (<8 m). Benjamin & Kaplan (2017) achieved sub-centimeter precision using a phase-shift laser distance meter with a floating target; while the present time-of-flight system exhibits slightly higher absolute error (±2.75 cm), it does so at a fraction of the cost and without requiring a cooperative target on the water surface. Compared with the drone-mounted Lidar system of García-López et al. (2023), which achieved an RMSE of ~5 cm for large-diameter wells, the proposed stationary device offers comparable accuracy with significantly lower capital and operational expenditure.

CONCLUSION

This study successfully designed, constructed, and field-validated a low-cost, non-contact groundwater level monitoring system that integrates a Lidar-Lite v3HP sensor, an Arduino Uno microcontroller, and an ESP8266 Wi-Fi module for real-time remote telemetry. Rigorous statistical comparison with manual tape measurements across two artesian wells demonstrated that the prototype delivers near-perfect linear correlation (r = 0.99995) and that a simple linear correction factor can substantially reduce RMSE by 40–75% and decrease systematic bias by approximately tenfold and threefold respectively for well 1 and well 2. With an upload latency of 33 seconds and a coefficient of variation below 1.21%, the system enables sub-minute monitoring frequencies that far exceed the temporal resolution of existing national networks. By leveraging open-source hardware and cloud-based IoT platforms, the device offers an economically viable, home-grown solution for expanding groundwater observation infrastructure in developing regions. The research represents a necessary step toward democratizing hydrometric data acquisition and strengthening evidence-based groundwater governance.

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