Journal of Geoscience and Environment Protection, 2026, 14(1), 142-158
https://www.scirp.org/journal/gep
ISSN Online: 2327-4344
ISSN Print: 2327-4336

Development of a Low-Cost IoT Based River Discharge Measurement System

Martin Wainaina Chege[1,2], Bartholomew T. Kuria[1,2], Arthur W. Sichangi[2], Moses M. Ngigi[2], Jason N. Kabi[3], Andreas Rienow[4]

[1]Remote Sensing Research Group (RSRG), Center for Spatial Information Science and Systems (CSISS), Institute of Geomatics GIS and Remote Sensing, Dedan Kimathi University of Technology, Nairobi, Kenya
[2]Institute of Geomatics GIS and Remote Sensing, Dedan Kimathi University of Technology, Nyeri, Kenya
[3]Center for Data Science and Artificial Intelligence (DSAIL), School of Electrical and Electronic Engineering, Dedan Kimathi University of Technology, Nyeri, Kenya
[4]Interdisciplinary Geographic Information Science, Institute of Geography, Ruhr-University Bochum, Bochum, Germany
Email: martinchegee@gmail.com

How to cite this paper: Chege, M. W., Kuria, B. T., Sichangi, A. W., Ngigi, M. M., Kabi, J. N., & Rienow, A. (2026). Development of a Low-Cost IoT Based River Discharge Measurement System. *Journal of Geoscience and Environment Protection, 14,* 142-158.
https://doi.org/10.4236/gep.2026.141009

Received: November 28, 2025
Accepted: January 19, 2026
Published: January 22, 2026

Abstract

Water scarcity is increasingly becoming a major concern globally. Impacts of climate change and human interference through abstraction have greatly contributed to the declining discharge within rivers, affecting sustainability. The impacts of declining river discharge are dire, impacting both upstream and downstream users and marine ecosystems. The impact of low discharge results in dried riverbeds and marine life death, among other critical environmental and human challenges. In Kenya, river discharge monitoring is mandated to the Water Resources Authority (WRA), which deploys river gauges and acoustic Doppler velocimeters, which are manual and lack telemetry. This has resulted in inadequate real-time river discharge data, endangering timely scientific investigations and policy-making decisions. To bridge this gap, an innovative real-time river discharge monitoring system that utilizes the Internet of Things was developed. The device encompasses three sensors: water level, flow sensor, and temperature. The sensors are interconnected in a 6 cm by 5 cm printed circuit board assembled with other auxiliary components. Arduino Nano lies at the heart of the interconnection of the sensors, and the Lora Module transmits the collected data to a cloud database. The PCB is housed in a 50 mm by 70 mm waterproof IP47 enclosure. The River Discharge Monitoring System operates by collecting data from the deployed location and transmitting it to the cloud spatial database, where it is geo-tagged. Key factors include water level, flow velocity, and temperature, which are continuously collected by the sensors and transmitted using LoRa. Field deployment demonstrated water level variations between 22 cm and 55 cm, temperature fluctuations from

19.50˚C to 20.23˚C with higher downstream temperatures, and discharge flows around 0.3 m^3/s, indicating below-average river flows. Validation against manual in-situ methods showed strong performance with a coefficient of determination (R^2) of 0.995 for discharge and 0.866 for water level, confirming the system's accuracy is comparable to traditional methods. Low root mean square error and mean absolute error values further support sensor reliability and low bias.

Keywords

Water, Internet of Things, Telemetry, Discharge, Geo-Enabled Monitoring

1. Introduction

Human, agricultural, and industrial processes rely on river water as a vital source (Rodell et al., 2009). However, due to recent environmental and climatic changes, river water management has become a formidable obstacle, particularly in regions where climate change has led to a reduced water supply. Measuring river discharge frequently and precisely is essential for water resource management, flood forecasting, and ecosystem conservation. River discharge, the volume of water that flows through a river channel per unit of time, is typically expressed in cubic meters per second, the sum of the river channel's cross-section, flow rate, and water level (Depetris, 2021).

In recent years the pressure on this precious commodity has been rising. Groundwater is being abstracted at far higher rates than it can be naturally replenished, and environmental and climatic changes have negatively impacted water availability (Bierkens & Wada, 2019). To balance the changing demand in water supply, there has been a rapid shift towards increased river abstraction, both legal and illegal within basins globally (Ngigi et al., 2008). Consequently, hydrological modelling Ávila et al., (2022) studies using earth observation data (Rodell et al., 2009) have revealed alarming global groundwater depletion rates (Tasoff, 2024).

Due to environmental and climatic changes, Kenya is experiencing unprecedented desertification (Odongo et al., 2025). This poses significant water management challenges in previously non-ASAL regions, resulting in severe water supply shortages. This situation has resulted in the loss of livelihoods, decreased crop yields, and increased food insecurity. Reservoirs, which are the primary source of reticulated water supply for agricultural and domestic use for many rural households, have dried up due to climate change. Consequently, there has been a dramatic increase in abstraction of rivers and streams to compensate for the water shortage (Dedan Kimathi University of Technology Enterprises Company (Dekutes), 2022). This trend is particularly evident in the Muringato catchment, where abstraction has risen, creating significant river water management challenges resulting in reduced water supply.

To manage this abstraction and shortage crisis it is paramount to ensure equitable and controlled distribution through sustainable abstraction, flood forecasting, and ecosystem conservation. Sustainable abstraction aligns with Sustainable Development Goals (SDG), particularly goal 6 on clean water and sanitation. However, studies show an excessive reliance on groundwater has caused continuous decline in water table (Rodell et al., 2009). Therefore, sustainable water management requires continuous and cost-effective river discharge monitoring systems.

Recent research has explored the application of the internet of things (IoT) in river water monitoring. Moreno et al., (2019) presented a study on IoT applications for monitoring water levels using cellular communication. They focused on the hardware development of the RiverCore and defined its applicability in a specific hydrological region of Colima, Mexico. The system utilizes MQTT architecture for transmission of the telemetry and 3G cellular networks for communication. The authors found the potential of the data generated by the monitoring network in reducing impacts of floods and providing valuable information for city planning. They further emphasized on the importance of building a reliable and low-cost water level monitoring network (Moreno et al., 2019). They, however, acknowledged data loss, which is accustomed to low cellular connectivity, and recommended further improvements on the RiverCore IoT device.

Similarly, Chowdury et al., (2019) developed a system for river monitoring using various sensors for quality assessment. The system collected data such as temperature, pH, turbidity, and ORP values with unique features sin frequency, mobility and power consumption for sustainability. The research demonstrated that integrating IoT with big data analytics enables real-time monitoring of water quality, enhancing public awareness and pollution mitigation. They recommended further systematic experimentation using technologies such as spark streaming analysis, deep learning neural network models, and belief rule-based systems for analyzing river water in Bangladesh (Chowdury et al., 2019).

Although several studies have explored IoT-based water monitoring systems, most have focused on water level or quality monitoring rather than direct river discharge measurement. Moreover, many of these systems, such as those developed by Chowdury et al., (2019) and Moreno et al., (2019) depend heavily on stable cellular networks and are designed for regions with advanced infrastructure. These limitations make their direct application challenging in rural and data-scarce environments such as the Muringato Catchment in Kenya.

Consequently, there remains a critical gap in the development of low-cost, reliable, and context-appropriate IoT systems capable of measuring river discharge in real time (Tahsin Fuad Hasan et al., 2024), particularly in areas with limited connectivity and financial resources. The lack of such systems has led to inadequate discharge data, hindering effective water abstraction monitoring, flood forecasting, and sustainable resource management. Addressing this gap is therefore essential to support equitable water distribution, safeguard ecosystems, and advance the Sustainable Development Goals (SDG 6) on clean water and sanitation (UNESCO, 2015).

2. Study Criteria

2.1. Study Area Description

The Muringato catchment is located in Nyeri County, Kenya, in the central highlands of Kenya (**Figure 1**), at an elevation of 1750 m above sea level. The catchment is lies between the Abadare ranges to the east and Mt. Kenya to the west, with its rivers flowing from the Abadare ranges, where their source is towards Mt. Kenya, where the system has been tested and deployed. The catchment forms part of the upper Tana basin, one of the 5 key Kenyan basins (**Figure 1**). The area experiences bimodal rainfall, with long rains of 1200 - 1600 mm from March to May and short rains of 500 - 1500 mm from October to December. The mean monthly temperatures range between 12.8˚C and 20.8˚C. Agriculture is the main economic activity within this region, comprising cash and food crops and the rearing of livestock and fish (Britannica, 2025). The main soil in the area is black cotton soil, which influences land use and drainage characteristics in the catchment.

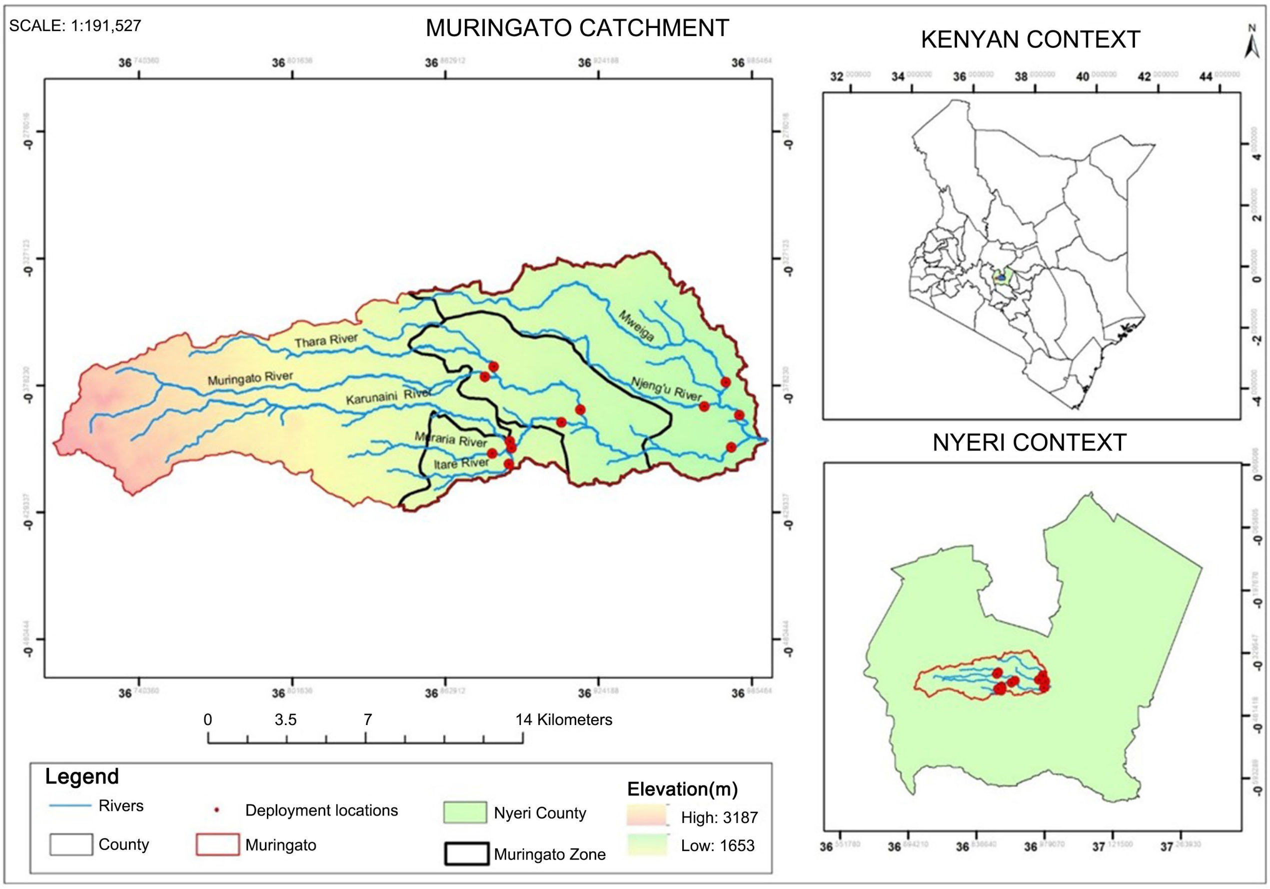


Figure 1. A study area map of Muringato Catchment located in Nyeri County, Kenya.

2.2. System Design and Methodology

The design and development follow a flow (**Figure 2**) for the realization of a deployable River Discharge Measurement System (RDMS). It comprises an Arduino nano microcontroller, an ultrasonic sensor, a flow sensor, and a temperature sensor. The Arduino nano is connected to other auxiliary components, such as the LoRa module, for communication and transmission of data collected (Klaus-Peter & Schell, 2023). On data collection by the sensor, it is transmitted to the Things Network (TTN) cloud; using custom web hooks, it is then transferred to a personal MySQL database, and subsequent requests are made every time data is ingested by the sensor to TTN.

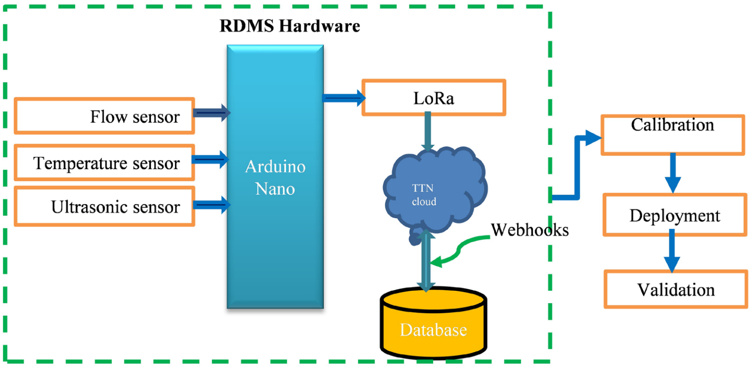


Figure 2. The architecture of the river discharge monitoring system showing the sensors and microcontroller system calibration deployment and validation.

The system's hardware was developed around an Arduino Nano microcontroller, which coordinates input and output signals from various sensors and communication modules. The circuit was designed using KiCad 7 software and implemented on a 5 cm × 10 cm etched copper board. The board interconnects the key components, including a YF-B6 flow sensor for measuring flow velocity and temperature, an ultrasonic sensor for determining water level, a DC power supply, and a battery voltage circuit for monitoring the system's power levels. The compact size and low power consumption of the Arduino Nano make it suitable for remote field installations with minimal maintenance.

The firmware was developed in the Arduino IDE, incorporating libraries for sensor operation, LoRa communication, and integration with The Things Network (TTN). The LoRa module enables long-range, low-power data transmission between the RDMS node and the TTN gateway. Data packets are sent from the sensors to TTN and automatically relayed to a custom MySQL database through a webhook. The RDMS webhook was configured to collect and transmit readings at 5-minute intervals, as discharge is a dynamic phenomenon, providing consistent temporal resolution suitable for data collection and transmission in near real-time for monitoring. The webhook serves as an HTTP endpoint that receives real-time data from TTN whenever new telemetry arrives. It performs automatic POST requests to the database, allowing continuous synchronization of sensor data with the local server without manual retrieval. This setup enables near real-time access and visualization of river discharge data and provides a scalable architecture for integrating multiple monitoring stations.

After the hardware and firmware assembly, the system calibration process was undertaken to ensure measurement accuracy and reliability before deployment. The calibration aimed to align the sensor outputs with known reference standards under controlled laboratory conditions. Each sensor—the ultrasonic, flow, and temperature sensors—was tested multiple times using independent measurement methods to confirm consistency and eliminate systematic errors.

For the ultrasonic sensor, distance range testing was carried out by positioning the sensor at distances of 100 cm, 200 cm, and 300 cm from a vertical wall, with continuous readings taken at each distance. These tests verified the accuracy of distance measurements and determined the sensor's error margin. For the flow and temperature sensors, calibration was performed in a water rig to simulate open-channel flow and later on a hydraulic workbench (F110) to simulate steady-state hydraulic conditions. The hydraulic workbench provided precise control of water flow and temperature, allowing verification of sensor responses under various flow rates and thermal conditions. The temperature sensor was further compared against a mercury thermometer to assess its accuracy and stability.

After successful calibration and functional verification, the RDMS prototypes were deployed along the Muringato River (**Figure 4**) in Nyeri County, Kenya. The deployment sites were selected based on accessibility, stable riverbanks, and representative flow conditions (Okeke et al., 2019). The RDMS units were mounted on rigid support frames to maintain consistent sensor orientation and minimize vibration interference. Power was supplied through a DC source and rechargeable battery unit, ensuring continuous operation. At each deployment site, the river width was measured manually with a measuring tape across the active channel. This value was then treated as a constant value during the monitoring period because the RDMS does not measure width dynamically.

Discharge (Q) was computed directly from the single-point velocity measured by the YF-B6 sensor using the simplified open-channel flow assumption:

$$Q = V_{\text{point}} \times A$$

where A = width × depth is the cross-sectional area of the river. This method assumes that the measured point velocity is a good representation of the flow in the channel. This is true for small to medium rivers with fairly uniform velocity profiles (Clasing & Muñoz, 2018). This prototype system did not use vertical velocity averaging or a correction factor.

During field validation, measurements obtained by the RDMS were compared with manual reference readings using a calibrated flow sensor, a mercury thermometer, and a measuring tape for water level assessment (Flemming, 1993). This validation confirmed that the field-deployed system produced accurate and consistent results, demonstrating its suitability for low-cost river discharge monitoring applications.

3. Results

The RDMS (**Figure 3**) device encompasses the three sensors: flow sensor, ultrasonic, and temperature. Additionally, the RDMS features a solar panel for recharge and a 3.7-volt, 6600 mAh lipo battery that is recharged by the 12-volt solar panels. With a protruding antenna, the RDMS uses it for transmission of data to the Things Network and consequently to personal databases using a webhook linked in the TTN dashboard.

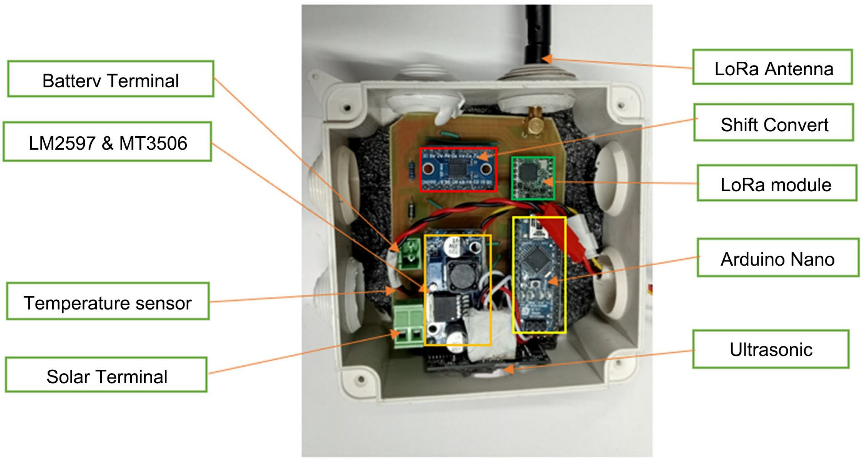


Figure 3. RDMS prototype system for data collection housed in a 100*100 mm enclosure. This features the three sensor module terminals, the microcontroller, the communication module, and the antennae housed in an enclosure.

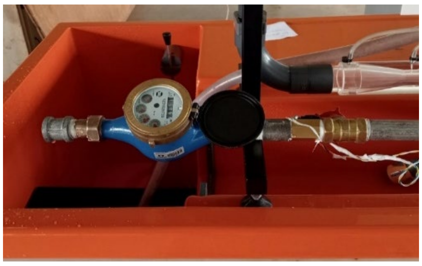
The RDMS prototype was deployed (**Figure 4**) along one of the rivers at latitude −0.41, longitude 36.97 that's covered with deep canopy cover; the system enclosure holding the PCB and the ultrasonic sensor and the solar panel was mounted on a wooden log at 3 feet from the floor of the stream. The flow sensor was immersed in water and mounted vertically with the sensor position parallel to the stream flow at 2 cm above the floor of the stream. The antennae of the communication module (LoRa) was positioned to face vertically for optimal signal transmission and command reception.

Figure 4. This is the deployed RDMS at the centerline, 140.2 cm from the river banks, of the river Muringato (0˚24'28.89"S, 36˚58'11.42"E) with real time telemetry being transmitted to the cloud (7th August 2025).

Prior to deployment, the system underwent calibration to ensure accurate and reliable measurements (Maag et al., 2016). The ultrasonic sensor was tested at distances of 100 cm, 200 cm, and 300 cm from a vertical wall, with continuous measurements taken at each distance to evaluate accuracy (**Figure 5**). Flow and temperature sensors were calibrated using a water rig to simulate open-channel flow and a hydraulic workbench (F110) to assess performance under controlled flow and thermal conditions (**Figures 6(a)-(c)**). During calibration, the flow sensor readings were compared with a standard water meter (Mohd Jais et al., 2024), and the temperature sensor was validated against a mercury thermometer. These calibration steps confirmed the precision and consistency of all sensors prior to field deployment.

Figure 5. Ultrasonic sensor distance range testing against a wall obstacle measurement for sensor performance over distances of 100 cm, 200 cm and 300 cm.

(a) (b)



(c)

Figure 6. (a) System simulation in a water rig for sensor operation testing; (b) hydraulic workbench flow sensor calibration process; and (c) a standardized water meter.

Field measurements collected during deployment included water level, flow rate, temperature, and battery voltage (**Figure 7**). Battery consumption was monitored throughout the deployment period, as the dense canopy cover reduced solar charging efficiency (**Figure 8**). The voltage measurements highlighted intermittent charging due to limited solar exposure, emphasizing the need for monitoring in shaded locations.

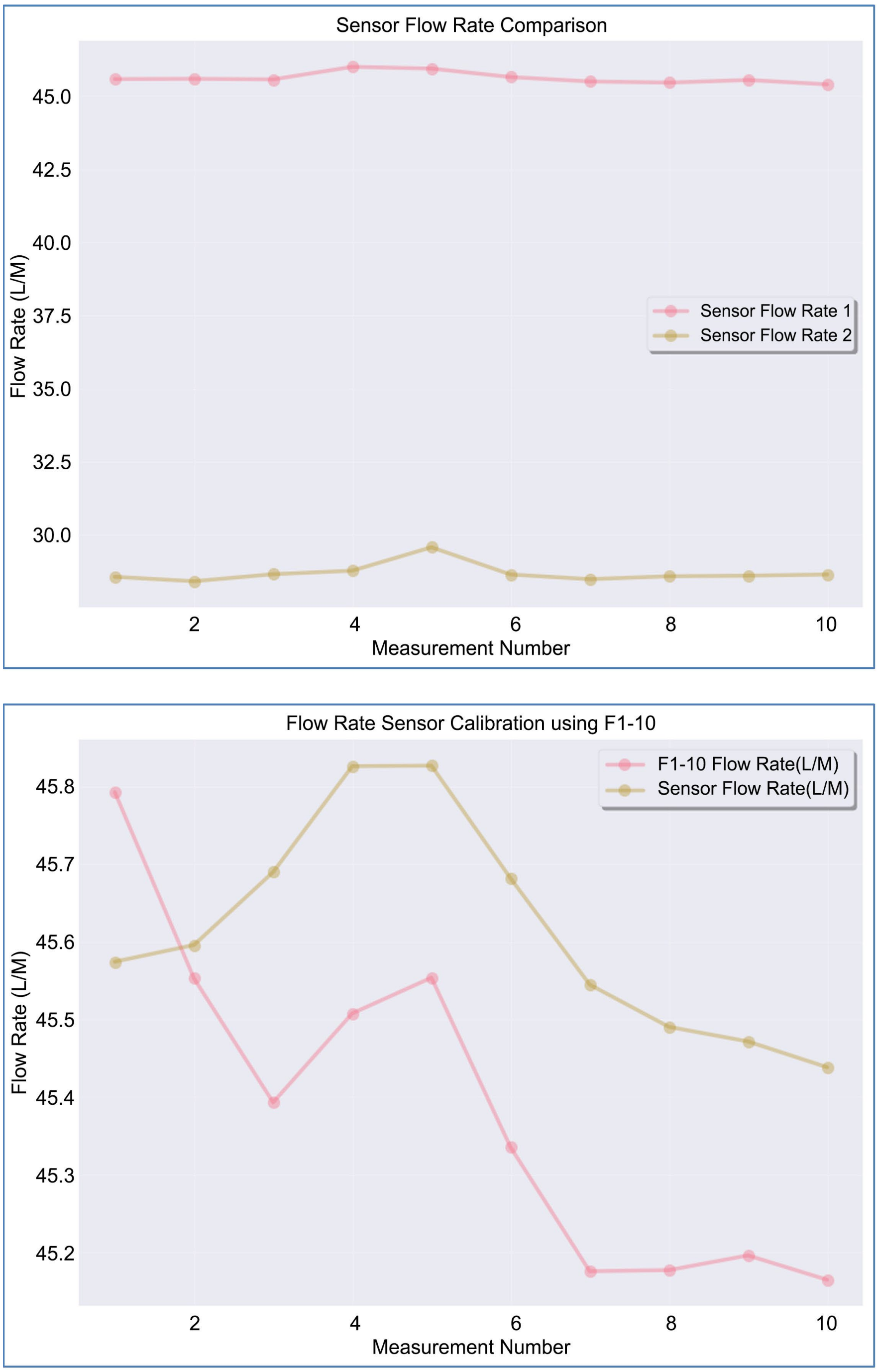


Figure 7. The velocity measurements between the flow rate sensor and the F1-10 were carried out at two different velocity measurements, showing a high level of correlation.

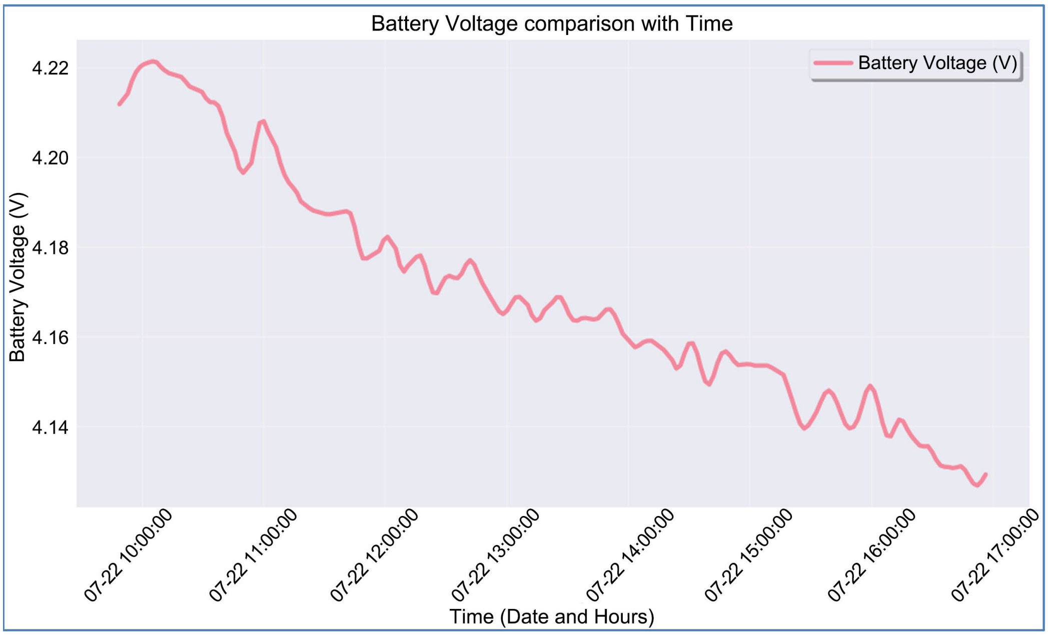


Figure 8. Battery usage discharge rate over time showing the voltage drop as well as the recharge duration over time using the solar panel.

Water level measurements ranged from 15 cm to 61 cm during the deployment, with variations likely due to upstream abstraction activities, such as water use by a coffee processing facility (**Figure 9**). Temperature readings from the onboard sensor ranged between 19.55˚C and 20.15˚C, with minor fluctuations attributed to solar penetration in the sensor location (**Figure 10**).

River discharge was calculated using the measured flow rate, water level, and stream width, according to:

$$\text{flow rate} * \text{level} * \text{width} = \text{Discharge}\ (Q) \quad (1)$$

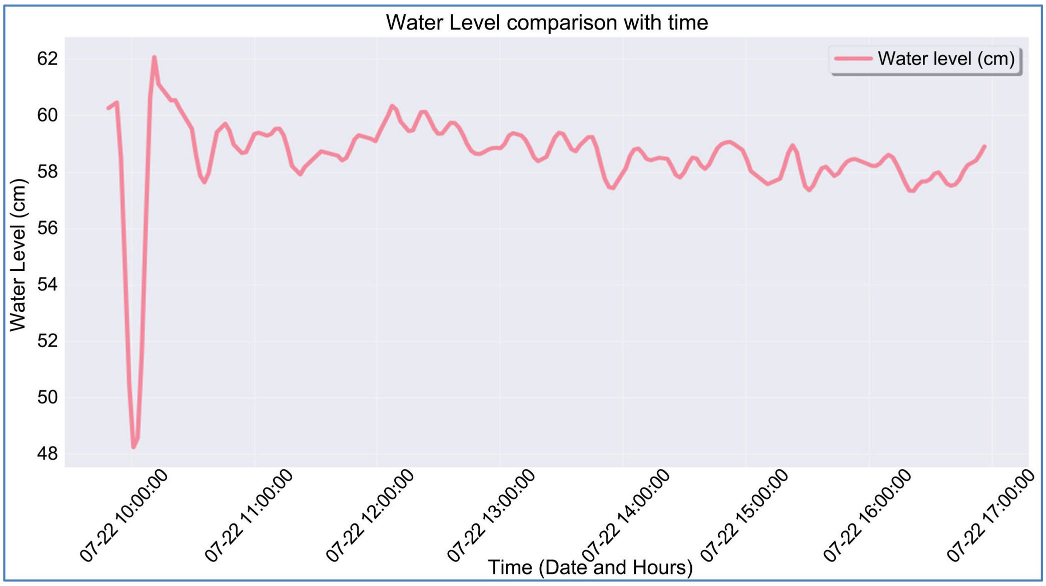


Figure 9. Water level data plotted against time.

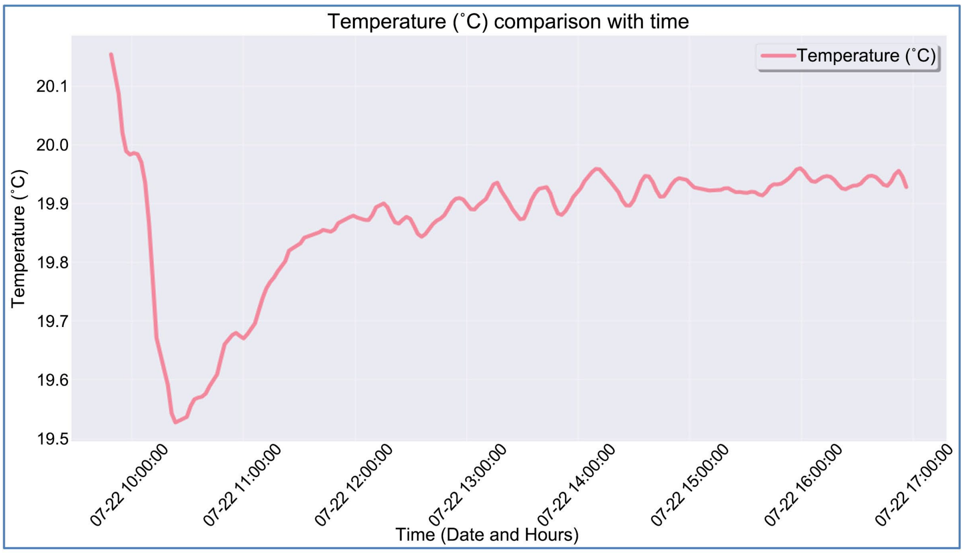


Figure 10. A graph of temperature against time over time for the deployment of the system.

The computed discharge data reflected low river flow during the observation period, consistent with stream width, season, and upstream abstraction impacts (**Figure 11**).

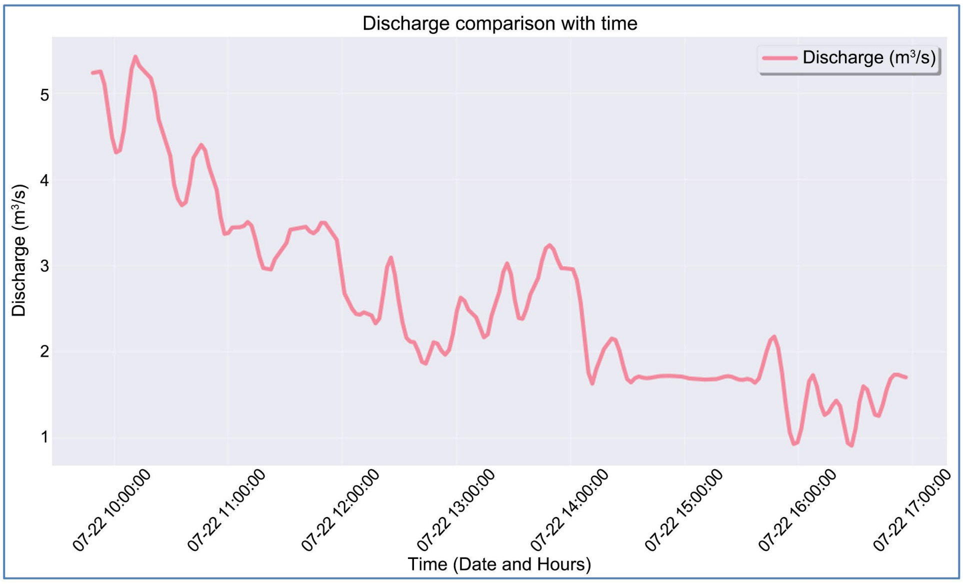


Figure 11. Discharge comparison over time.

The deployment confirmed that the RDMS could reliably capture continuous, high-frequency river discharge data with minimal human intervention. The system successfully transmitted telemetry via LoRa to TTN and through a webhook to a personal database, demonstrating the feasibility of a low-cost, IoT-based river monitoring system suitable for field applications. Further, after the stepwise validation (**Table 1**) of the system was carried out R^2 of the system was carried out (**Figure 12**).

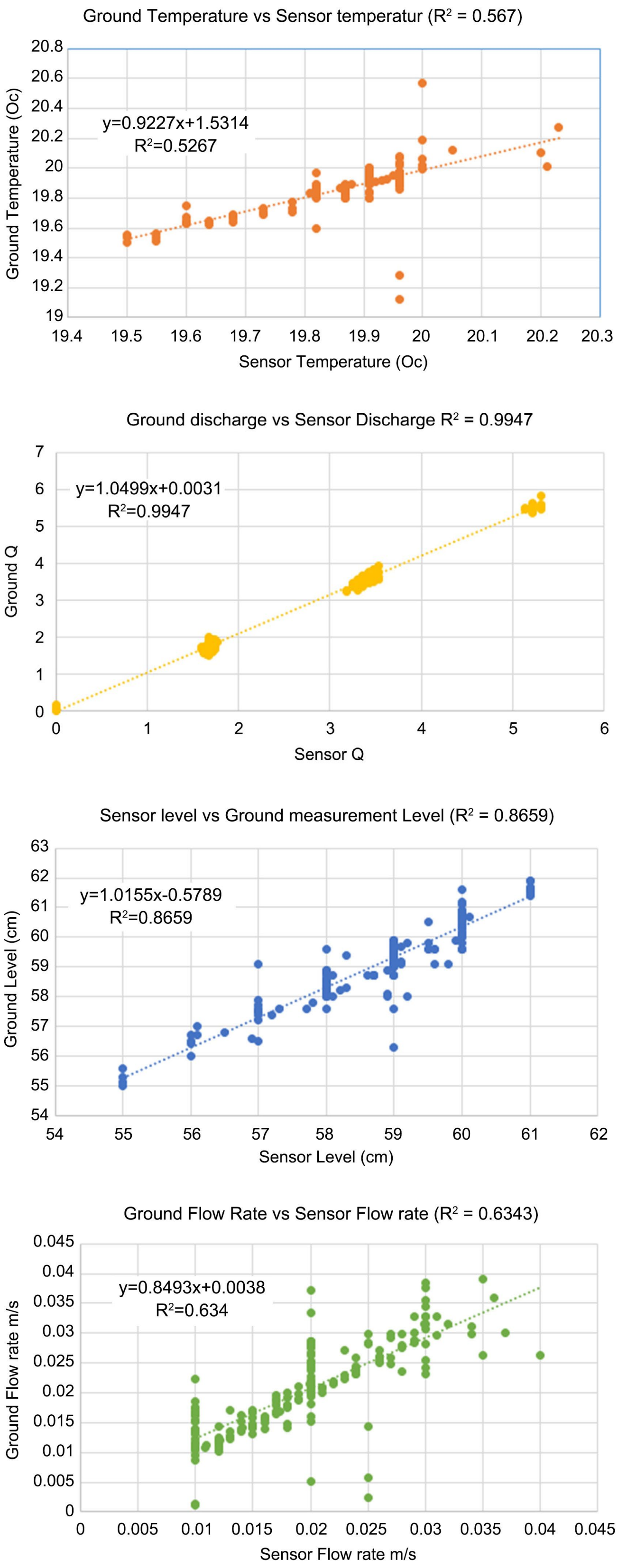


Figure 12. Validation results for temperature, discharge, water level and flow rate measurements.

Table 1. Tabular representation of the validation results of the 4 parameters of the system.

	Temperature	Level	Flow Rate	Discharge
Root Mean Square Error	0.102	0.606	0.005	0.171
R2	0.527	0.866	0.634	0.995
RMSE	0.001	0.001	0.000	0.009
MAE	5.49451E−05	0	2.74725E−06	0.0003
MBE	0	−0.0005	2.41758E−05	−0.0003
MSE	5.49451E−07	0.004	9.28571E−09	1.97802E−05

The validation results in Table 1 show that the regression model performs very well for discharge and water level, with high R^2 values of 0.995 and 0.866, respectively, indicating strong predictive capability. Temperature and flow rate have moderate R^2 values around 0.527 and 0.634, suggesting acceptable but less accurate predictions. The low root mean square errors (RMSE) and mean absolute errors (MAE) across all parameters demonstrate that the model's predictions closely match observed values with minimal average deviation. Additionally, the near-zero mean bias error (MBE) values indicate the model is unbiased, neither consistently overestimating nor underestimating. Overall, the system shows reliable performance, particularly for discharge and water level, while there is room for improving temperature and flow rate predictions.

4. Discussion

The validation results from this study demonstrate that the developed River Discharge Monitoring System (RDMS) performs reliably for measuring discharge and water level, with R^2 values of 0.995 and 0.866 respectively, indicating strong agreement with reference measurements. These methodologies yielded high accuracy in river discharge monitoring (Manches et al., 2025) The moderate performance on temperature ($R^2 = 0.53$) and a flow rate ($R^2 = 0.63$) aligns with challenges often reported in capturing highly dynamic environmental parameters, where sensor sensitivity and natural variability can affect precision.

Compared to established hydrological methods, such as current meter and float techniques commonly used in stream discharge assessments, the RDMS' integration of low-cost sensors and IoT-based data transmission provides a comparable level of discharge measurement accuracy while offering advantages in real-time monitoring and remote deployment (Essamlali et al., 2024). Traditional methods, though reliable, involve labor-intensive fieldwork and infrastructure, which may be impractical for continuous measurements in resource-limited rural settings like the Muringato Catchment.

The system's low root mean square error (RMSE) and mean absolute error (MAE) across all parameters indicate good calibration and minimal prediction bias, supporting its suitability for real-time river management applications. The near-zero-mean bias error (MBE) values confirm that the system does not systematically over or underestimate key variables, a critical aspect for sustainable water resource management and flood forecasting.

Despite these results, the moderate R^2 values for temperature and flow rate suggest that further sensor enhancements or multi-sensor data fusion techniques could improve the system's overall performance. This is in line with recommendations from previous IoT-based aquatic monitoring studies emphasizing continuous refinement to overcome environmental noise and sensor limitations (Chowdury et al., 2019; Moreno et al., 2019).

5. Limitations

While the RDMS demonstrates strong potential for low-cost river discharge monitoring, several limitations were observed during design, development, and field deployment. First, sensor operation efficiency can be affected by environmental conditions such as stream debris pileup in the sensor, soil and rocks deposition, which may lead to erroneous readings in high turbid rivers streams. Regular maintenance or the integration of self-cleaning mechanisms and developing AI solutions to detect anomalous data collection may be required to ensure consistent data quality.

Second, operational durability remains a challenge during high-flow or flood events. Strong currents, floating debris, and bank erosion can physically damage or displace the sensor housing, posing risks to long-term deployment. Designing more robust mounting structures or using protective casings could improve resilience.

Third, the reliance on battery power and solar charging introduces additional constraints. In densely vegetated riparian zones, canopy cover can limit solar panel exposure, reducing charging efficiency and potentially causing power interruptions. This highlights the need for optimized power management strategies or alternative energy solutions for heavily forested environments.

Finally, the reliability of LoRaWAN transmission may change based on the terrain, the plants around it, and how far away the nearest TTN gateway is. In areas with a lot of trees or complicated terrain, signal loss can cause data loss or transmission intervals that aren't regular. This means that gateway densification or hybrid communication solutions may be needed.

In summary, the RDMS prototype offers a promising low-cost, scalable solution for regular river discharge monitoring, particularly suited to data-scarce, rural environments. It bridges the gap between laborious traditional methods and the need for cost-effective, reliable hydrological data to support sustainable abstraction, ecosystem conservation, and achievement of SDG 6 targets (UNESCO, 2015) in Kenya and similar context globally.

6. Recommendations

Based on the system development, deployment, initial calibration and validation results, it has been proved that it generates reliable data that can be utilized in the monitoring of the stream flow parameters. This calls for the need to have a higher density of sensors in the entire catchment for more discharge monitoring capabilities, stream health determination, and information management. With decreasing river gauges poses a threat to stage measurement and with the densification of the network poses a better solution to the data archiving and collection across the catchment.

Beyond data collection, real-time information generated by a series of networks of RDMS units has direct added operational value for water resources management authorities. Continuous discharge and water level measurements can support the Water Resources Authority (WRA) and local WRUAs in setting scientifically informed abstraction limits based on current flow conditions, especially during dry seasons, while near real-time stage monitoring can strengthen early warning systems by enabling the rapid detection of rising water levels, thereby supporting the timely issuance of flood alerts to at-risk communities. Additionally, long-term datasets from multiple stations bridge the data gap and can guide catchment restoration priorities, drought planning, and licensing decisions by providing accurate, spatially distributed hydrological evidence.

The RDMS portrays the need to continuously undertake research and development within the hydrology field for ecosystem monitoring; continuous improvement of the system performance is paramount to archiving reliable data for modeling of the catchment and hence the need to continuously undertake system calibration and validation.

With the community engagement, there is need to continuously engage the community for tool development, testing and validation, as well as training on the use of these tools for the sustenance of their catchment health through the locals and Water Resources Users Associations (WRUAs).

Design Files Availability

The design files for the IoT are available upon request and will be made available on MIT license through a GitHub repository.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

References

Ávila, L., Silveira, R., Campos, A., Rogiski, N., Gonçalves, J., Scortegagna, A. et al. (2022). Comparative Evaluation of Five Hydrological Models in a Large-Scale and Tropical River Basin. *Water, 14,* Article 3013. https://doi.org/10.3390/w14193013

Bierkens, M. F. P., & Wada, Y. (2019). Non-Renewable Groundwater Use and Groundwater Depletion: A Review. *Environmental Research Letters, 14,* Article 063002. https://doi.org/10.1088/1748-9326/ab1a5f

Britannica (2025). *Mount Kenya, Coffee, Tea.* Britannica. https://www.britannica.com/place/Nyeri

Chowdury, M. S. U., Emran, T. B., Ghosh, S., Pathak, A., Alam, M. M., Absar, N. et al.

(2019). IoT Based Real-Time River Water Quality Monitoring System. *Procedia Computer Science, 155,* 161-168. https://doi.org/10.1016/j.procs.2019.08.025

Clasing, R., & Muñoz, E. (2018). Estimating the Optimal Velocity Measurement Time in Rivers' Flow Measurements: An Uncertainty Approach. *Water, 10,* Article No. 1010. https://doi.org/10.3390/w10081010

Depetris, P. J. (2021). The Importance of Monitoring River Water Discharge. *Frontiers in Water, 3,* Article ID: 745912. https://doi.org/10.3389/frwa.2021.745912

Dedan Kimathi University of Technology Enterprises Company (Dekutes) (2022). Abstraction Survey Report.

Essamlali, I., Nhaila, H., & El Khaili, M. (2024). Advances in Machine Learning and IoT for Water Quality Monitoring: A Comprehensive Review. *Heliyon, 10,* e27920. https://doi.org/10.1016/j.heliyon.2024.e27920

Flemming, N. (1993). Manual of Quality Control Procedures for Validation of Oceanographic Data. *IOC Manual and Guides.* UNESCO.

Maag, B., Saukh, O., Hasenfratz, D., & Thiele, L. (2016). *Pre-Deployment Testing, Augmentation and Calibration of Cross-Sensitive Sensors.* https://www.researchgate.net/publication/311494636_Pre-Deployment_Testing_Augmentation_and_Calibration_of_Cross-Sensitive_Sensors

Klaus-Peter, N., & Schell, H. (2023). *Building an ad Hoc Network with LoRa and Transferring Field Data to the Internet.* ResearchGate. https://www.researchgate.net/publication/368925753_Building_an_ad_hoc_network_with_LoRa_and_transferring_field_data_to_the_internet

Manches, A., Nygren, M., Price, S., & Revueltas Roux, A. (2025). Challenges of Translational Education Research: Teachers' Interpretations of Embodied Learning. *Cogent Education, 12,* Article 2490443. https://doi.org/10.1080/2331186x.2025.2490443

Mohd Jais, N. A., Abdullah, A. F., Mohd Kassim, M. S., Abd Karim, M. M., M, A., & Muhadi, N. (2024). Improved Accuracy in IoT-Based Water Quality Monitoring for Aquaculture Tanks Using Low-Cost Sensors: Asian Seabass Fish Farming. *Heliyon, 10,* e29022. https://doi.org/10.1016/j.heliyon.2024.e29022

Moreno, C., Aquino, R., Ibarreche, J., Pérez, I., Castellanos, E., Álvarez, E. et al. (2019). Rivercore: IoT Device for River Water Level Monitoring over Cellular Communications. *Sensors, 19,* Article 127. https://doi.org/10.3390/s19010127

Ngigi, S. N., Savenije, H. H. G., & Gichuki, F. N. (2008). Hydrological Impacts of Flood Storage and Management on Irrigation Water Abstraction in Upper Ewaso Ng'iro River Basin, Kenya. *Water Resources Management, 22,* 1859-1879. https://doi.org/10.1007/s11269-008-9257-5

Odongo, R. A., Schrieks, T., Streefkerk, I., de Moel, H., Busker, T., Haer, T. et al. (2025). Drought Impacts and Community Adaptation: Perspectives on the 2020-2023 Drought in East Africa. *International Journal of Disaster Risk Reduction, 119,* Article 105309. https://doi.org/10.1016/j.ijdrr.2025.105309

Okeke, C. A. U., Ede, A. N., & Kogure, T. (2019). Monitoring of Riverbank Stability and Seepage Undercutting Mechanisms on the IJU (Atuwara) River, Southwest Nigeria. *IOP Conference Series: Materials Science and Engineering, 640,* Article 012105. https://doi.org/10.1088/1757-899x/640/1/012105

Rodell, M., Velicogna, I., & Famiglietti, J. S. (2009). Satellite-Based Estimates of Groundwater Depletion in India. *Nature, 460,* 999-1002. https://doi.org/10.1038/nature08238

Hasan, T. F., Kabashi, N. A., Saleh, T., Alam, M. Z., Wahab, M. F., & Hamid Nour, A. (2024). Water Quality Monitoring Using Machine Learning and IoT: A Review. *Chemi-*

cal and Natural Resources Engineering Journal (Formally known as Biological and Natural Resources Engineering Journal), 8, 32-54. https://doi.org/10.31436/cnrej.v8i2.100

Tasoff, H. (2024). Global Groundwater Depletion Is Accelerating, but Is Not Inevitable. *The Current.* https://news.ucsb.edu/2024/021303/global-groundwater-depletion-accelerating-not-inevitable

UNESCO (2015). *Goal 6: Clean Water and Sanitation.* The Global Goals. https://globalgoals.org/goals/6-clean-water-and-sanitation/