Waterlines, 44:1, 119–135

IoT-Enabled Real-Time Water Quality Surveillance and Decision Support Systems for Sustainable Rural WASH Infrastructure Management

Ajit Bhosale, Sandeep Musale, Ashok Khedkar,
Mahendra Deore

Abstract: *Rural drinking-water services increasingly use continuous monitoring, yet many deployments stop at dashboards and do not lead to feasible operations and maintenance actions. A key gap, in the evaluated setting, is the absence of an end-to-end specification that connects near-real-time water-quality signals to accountable decision owners, action owners, and closure evidence under intermittent connectivity and sensor drift. To address this gap, a decision-first conceptual framework is presented that organizes an IoT-enabled stack from monitoring objectives through sensing, transfer, data assurance, interpretation, alerting, tasking, escalation, verification, closure, and a learning loop. The framework is anchored to 3-5 recurring decision archetypes and defines minimum signals, quality assurance and quality control gates, tiered alert severity, and audit-ready workflow records. It also provides an evaluation checklist that separates monitoring-only deployments from decision support, with particular attention to common failure modes that prevent alerts from translating into owned actions and verifiable closure. Health impacts are not claimed without outcome evaluation. In practical settings, the approach can guide the design and audit of rural WASH management systems for real-world use by service managers and implementers.*

Keywords: Water Quality Surveillance, Rural WASH Services, Decision Archetypes, Workflow Triggering, Conceptual Framework, Rural Service Managements

---

Ajit Bhosale (ajit.bhosale@cumminscollege.in), Department of Mechanical Engineering, Cummins College of Engineering for Women Pune, India
Sandeep Musale (sandeep.musale@cumminscollege.in), Department of E and TC, Cummins College of Engineering for Women Pune, India.
Ashok Khedkar (ashok.khedkar@cumminscollege.in), Department of E and TC, Cummins College of Engineering for Women Pune, India.
Mahendra Deore (mahendra.deore@cumminscollege.in), Department of Computer Engineering Cummins College of Engineering for Women Pune, India.

ISSN: 0262-8104 (print) 1756-3488 (online)

Introduction: the monitoring-to-action gap

Internet of Things (IoT) sensing is increasingly used in water resources to collect water quality data at higher frequency and lower cost, yet many deployments still end at monitoring and visualization (Ansari & Vidyarthi, 2025). In rural water, sanitation, and hygiene (WASH) services, intermittent power, connectivity, and limited staffing make this breakdown more consequential in practical settings. AI-IoT surveys often emphasize analytics while under-specifying the decision workflow that turns data into field action (Ansari & Vidyarthi, 2025; Miller et al., 2025). Fig. (1) summarizes how the monitoring-to-action gap emerges.

This study reframes water quality surveillance as decision infrastructure that links measurements to named actions and closure evidence. Many IoT and machine learning systems fail to close the response loop because alerts are not connected to feasible field tasks, escalation, and verification (Alprol et al., 2024). The framework previews a decision-first blueprint spanning data assurance, tiered alerting, task assignment, and auditable closure, with real-time defined by latency bands that match rural action windows for real-world use. No health outcome claims are made.

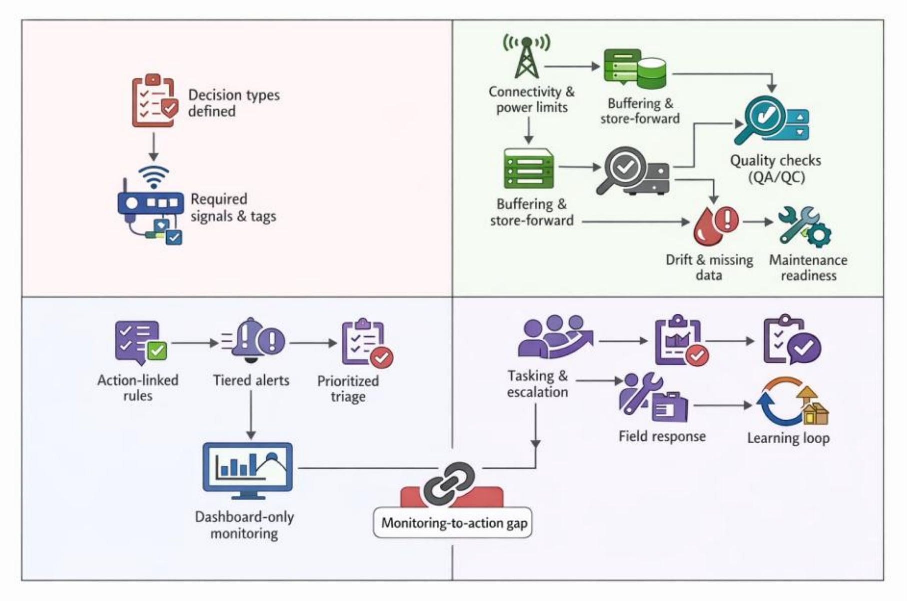

Figure 1. Monitoring-to-action gap in rural WASH

Definitions, scope, and what real-time means here

This study defines Internet of Things (IoT)-enabled water quality surveillance as an end-to-end stack that integrates sensing, connectivity, data handling, assurance checks, and decision outputs (Ayaz et al., 2019; Morchid et al., 2023). Here, surveillance means repeated monitoring to support management decisions, rather than compliance-only laboratory testing, while decision support refers to the rules and workflow for assignment, escalation, verification, and closure. Total time to action is defined as the sum of data, decision, and response latencies in Eq. (1).

$$L_{total} = L_{data} + L_{decision} + L_{response} \tag{1}$$

Real-time is specified in three latency bands, Minutes, Hours, and Days, each linked to feasible rural actions in Tab. (1). Scope boundaries are summarized in Fig. (2) (Ayaz et al., 2019; Elijah et al., 2018). Within this framework, system scope covers rural drinking-water assets and the full data-to-action chain from sensing through alerting, tasking, and closure, with roles separated across sensing, connectivity, and analytics (Ayaz et al., 2019; Elijah et al., 2018). Out of scope are wastewater monitoring, irrigation and aquaculture, river ecology, and smart agriculture (Elijah et al., 2018). Sustainability is defined as long-run service continuity and maintainability within local institutions.

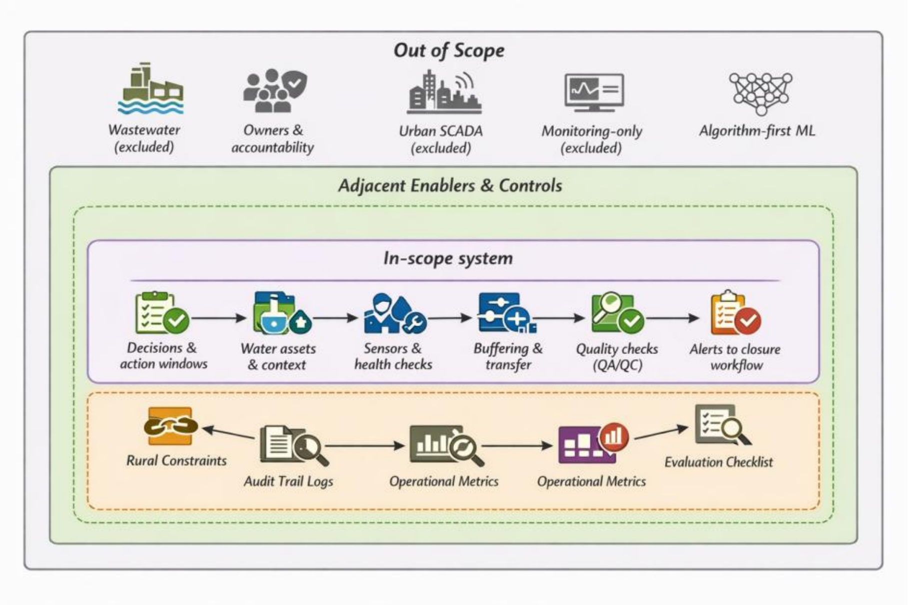

Figure 2. Scope and real-time boundaries

Table 1. Latency bands mapped to action windows

Latency Band	*Decision And Response Use*	*Example Feasible Rural Actions*
Minutes	Rapid triage when quick response is feasible (align data latency, decision latency, and response time to a minutes-scale action window)	Send alert, place in triage queue, assign actor, trigger escalation if severe
Hours	Same-day decision support when travel and staffing constraints make immediate response unlikely	Prioritize across assets, issue maintenance prompt, schedule dispatch, prepare parts and consumables
Days	Planned action and verification when connectivity, calibration burden, or field access delays are expected	Schedule maintenance and calibration, verify and close tasks, update thresholds and maintenance schedules in learning loop

Rural WASH operations and common failure modes

In rural water, sanitation, and hygiene (WASH) systems, services are commonly delivered through many small, dispersed water points, with operation and maintenance constrained by limited staff, long travel times, and irregular supply chains. Where treatment is used, it often consists of basic filtration and disinfection, and performance depends on routine upkeep and appropriate operating conditions (Yao et al., 1971). For deployment in practical settings, these constraints determine what can be monitored and which post-alert actions are realistic.

Breakdowns recur when monitoring is introduced without a resourced decision and response chain, leaving unclear decision ownership, no duty roster for triage, missing spare parts or consumables, and records too weak to support escalation and closure. Technical failure modes add to this gap, including intermittent power or connectivity, sensor drift or fouling, and missing data that can produce noisy alarms and alert fatigue. Actionability is also limited when source-water conditions are complex or rapidly changing but surveillance provides too little process context to translate signals into concrete field steps (Leenheer & Croué, 2003).

Water Safety Plan-style risk management fits decision support because it begins with hazards, control measures, and corrective actions, not instruments alone. Within this framing, a monitoring-to-action chain can be defined through accountable roles, action windows, verification evidence, and learning loops that update rules and maintenance priorities as conditions change.

Decision-first data-to-action reference model

The reference model connects near-real-time water-quality sensing to accountable rural water, sanitation and hygiene (WASH) actions by defining data assurance, alert rules, task assignment, escalation, field response, and verified closure, and then incorporating a learning loop that updates thresholds and maintenance plans in settings with intermittent connectivity (Et-taibi et al., 2024). Fig. (3) outlines this decision-first chain from telemetry to validated outcomes, emphasizing confirmed action and closure rather than dashboards alone.

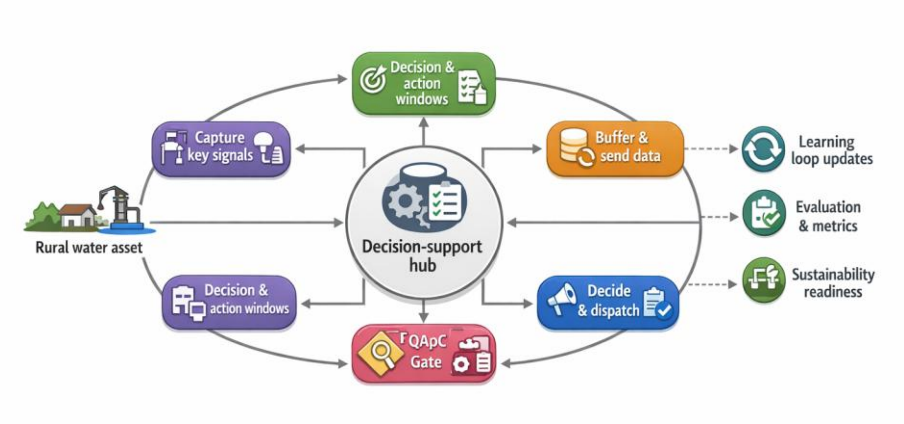

Figure 3. Decision-first data-to-action chain

Chain stages from monitoring objective to closure

A reliable rural water-quality surveillance system begins by translating a monitoring goal into a specified decision-to-action chain, with a defined action window and named responsibility. Monitoring objectives should be expressed as decision archetypes that identify the decision owner, action owner, feasible actions, and the closure evidence that proves completion. Sensing and context capture then generate time-stamped observations linked to an asset, combining water-quality readings with location and identity tags and sensor or system health telemetry.

Before any alerting, data assurance should produce quality flags that determine what is permitted to trigger action in practical settings, including plausibility checks, drift or fouling indicators, rules for missing-data handling, and calibration status. The alert-to-closure workflow should then package the alert payload with severity and persistence checks, create a task record with an assigned actor, action type, and response time, and document escalation, verification status, and closure. Tab. (2) consolidates these required artifacts so that monitoring remains accountable to feasible, timely responses for real-world use.

Table 2. Stage artifacts for measurement to closure

Chain Stage	***What It Produces***	***Required Artifacts***
Monitoring Objectives	Clear decisions tied to rural action windows	Decision archetypes with decision owner, action owner, action window, feasible actions, closure evidence
Sensing And Context Capture	Time-stamped observations linked to the right asset	Water-quality readings, sensor or system health telemetry, context tags (asset identity, location)
Data Assurance Before Alerting	Quality flags that gate what can trigger action	Plausibility checks, drift or fouling flags, missing-data handling rules, calibration status
Alert To Closure Workflow	Auditable record from alert to verified completion	Alert payload (including severity and persistence checks), task record (assigned actor, action type, response time), escalation record, verification status, closure record

Actors, artifacts, and the learning loop

Accountability in practical settings depends on defined roles and records along the data-to-action chain: a decision owner to approve alert rules, an action owner to receive and complete tasks, and a verifier to confirm outcomes and close cases. The minimum artifacts are an alert record, a timestamped task assignment, an escalation log, and closure evidence linked to the asset and quality-assurance flags. A learning loop periodically reviews closures, false alerts, and maintenance events to update thresholds, calibration plans, and responsibilities.

Recurring decision archetypes for rural services

The framework is organized around recurring decision archetypes that connect measurements to operational actions, including investigating abnormal quality within hours, adjusting treatment dosing within minutes to hours, issuing safe-use advisories within a day, scheduling maintenance for drift or fouling within days, and confirming closure through follow-up readings and field logs.

Archetypes and action-window ladder

In rural settings, decision support is organized around four decision archetypes that make the data-to-action chain explicit: urgent water quality alerts with advisories, asset inspection with corrective maintenance, sensor or system health maintenance for calibration or fouling, and cross-asset triage under limited staff and transport. Required definitions for owners, windows, and closure evidence are summarized in Tab. (3).

Timeliness is set by the action window for each archetype, spanning minutes, hours, or days, and must account for data latency, decision latency, and response time under intermittent connectivity. Fig. (4) links detection, triage, response, and verification to these windows, so real-time is evaluated by whether the workflow achieves verified closure before the window expires.

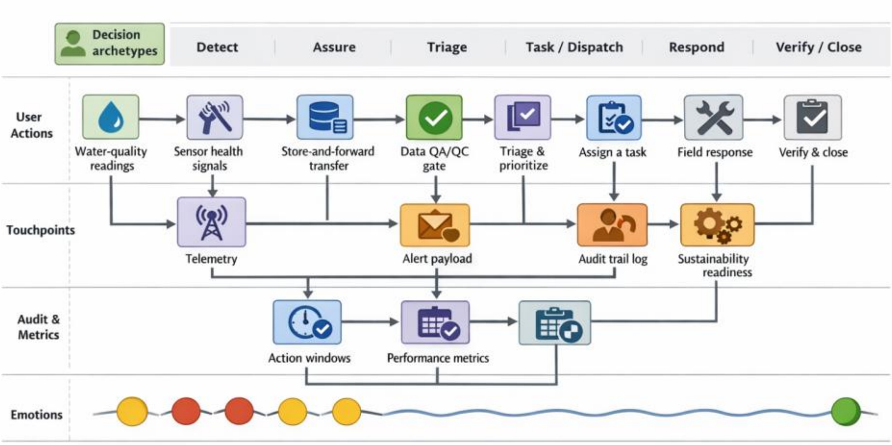

Figure 4. Action windows across decision archetypes

Table 3. Archetypes with owners, actions, closure

Archetype Element	*What Must Be Defined*	*Why It Matters*
Decision Owner	Named person or role accountable for the decision rule and when it is triggered	Prevents monitoring without an accountable decision chain
Action Owner	Named person or role responsible for carrying out the response, including assignment and escalation	Enables tasking, escalation, and accountability
Action Window	Time window tied to feasible rural response (minutes, hours, days), linked to data latency, decision latency, and response time	Sets realistic timeliness targets and defines what real-time means operationally
Feasible Actions	Practical response steps the team can execute under rural constraints (staffing, transport, connectivity, power, calibration burden)	Keeps decision support focused on actions that can actually be done
Closure Evidence	Recorded verification or closure status in the workflow log, with an auditable trail of assignment, escalation, and closure	Allows verification and closure rate checks and supports auditing and learning updates

Minimum signals, QA gates, and decision outputs

Each decision archetype should specify minimum signals for deployment in monitoring: a water quality reading (e.g., turbidity), asset identity, time stamp, and system health telemetry (battery and connectivity). Before alerting, QA gates should filter failure cases including implausible values, missing-data runs, and indications of drift or fouling, consistent with monitoring design guidance (Lambert & Gilbert, 1988) and turbidity sensing practice (Govindarajan et al., 2025).

Explainable rules should map QA-passed signals to a tiered output (triage entry, task, or advisory) with an action owner and action window. Escalation should require persistence.

Closure should be logged as verification, such as a follow-up reading returning to range or a completed maintenance record. Predictive models, when used, should maintain driver attribution and auditability (Lambert & Gilbert, 1988; Makumbura et al., 2024).

Design requirements for decision infrastructure

For each archetype, decision infrastructure must specify decision owners, action owners, action windows, and closure evidence. In practice, systems must capture asset identity, water quality and sensor health signals, buffer data for intermittent networks, run quality assurance and control checks before alerting, issue tiered alerts with assignment and escalation, and log actions and verification.

Technical and data assurance stack under constraints

Parameter selection and sensing cadence should be matched to the management decision and its action window, rather than relying on high-frequency sampling that cannot be acted on in practical settings. In rural contexts with limited power and maintenance, sensor reliability depends on low-power duty cycling, stable mounting, and calibration routines that can realistically be carried out, consistent with Internet of Things (IoT) sensing reviews (Silva et al., 2025).

Designing for **intermittent first connectivity** requires local buffering of observations and store-and-forward transfer, with time stamps and asset identifiers that remain reliable across delays. The sensing-to-delivery stack is outlined in Fig. (5). Platform choices should also reflect interoperability, security, and data-sharing constraints, while keeping data handling lightweight and auditable (Gomes et al., 2020; Popescu et al., 2024).

Alerts should be issued only after quality assurance (QA) and quality control (QC) checks that directly target common failure modes, including implausible values, drift or fouling, out-of-date calibration status, missing-data gaps, and degraded system-health telemetry. These pre-alert gates are summarized in Tab. (4). Short-term noise can be reduced with a rolling mean before gating, Eq. (2).

$$\overline{x_t} = \frac{1}{m}\sum_{i=0}^{m-1} x_{t-i} \qquad (2)$$

helps suppress spurious alerts that would otherwise consume limited response capacity.

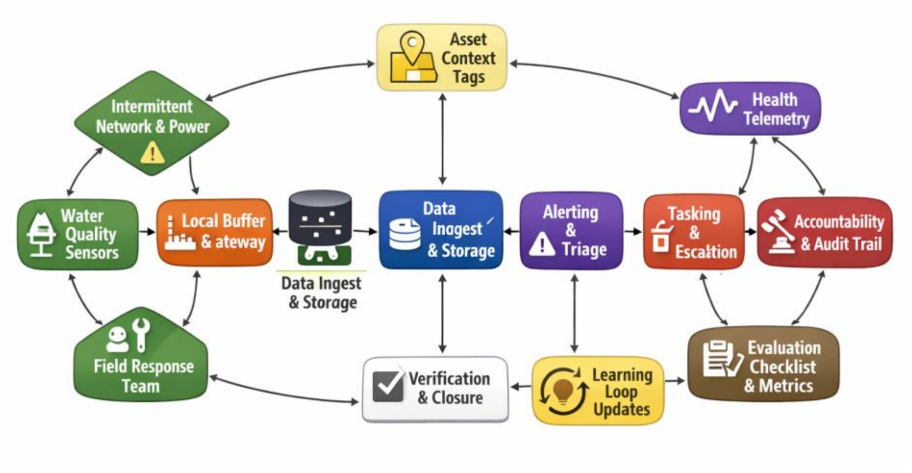

Figure 5. Intermittent-first IoT decision stack

Table 4. QA gates for drift, fouling, missingness

Gate	***What To Check***	***Before Alerting, Do This***
Plausibility check	Water-quality readings for plausibility	Apply plausibility checks before any alert is created
Drift or fouling flag	Sensor drift or fouling indicators	Flag drift or fouling and gate alerts on these flags
Calibration status	Calibration status for the sensor stream	Use calibration status as a QA condition before alerting
Missing-data handling	Missing data and data gaps	Apply missing-data handling rules before triggering alerts
System health telemetry	Battery status, uptime, connectivity success or failure indicators	Use system-health signals as QA inputs before alerting

Alert-to-task workflow, escalation, and verification

Alerts should be issued only after quality assurance and should include a defined payload comprising an asset identifier, location, timestamp, parameter values, health flags, an action window, and a severity tier. To reduce alert fatigue in practical settings, persistence checks, rate limits, and aggregation can be applied so that repeated anomalies are consolidated into one actionable task, consistent with dashboard-plus-control patterns (Morchid et al., 2026).

Each alert must generate an assigned task and an escalation path when connectivity or staffing delays response. Offline field use requires cached instructions and store-and-forward updates. Completion requires verification evidence and closure recording, because automation claims lack credibility without documented follow-through and auditability in field conditions (Morchid et al., 2026).

Evaluation checklist for true decision support

The evaluation checklist tests whether an IoT-enabled water quality surveillance deployment functions as decision support that is timely, actionable, accountable, and sustainability-ready, rather than monitoring alone. It applies a multi-criterion assessment by scoring criteria across the data-to-action chain (Pena-Pereira et al., 2020).

The checks follow a framework. They start by defining decision archetypes with named owners, feasible actions, action windows, and closure evidence, then confirm that observations include both water quality readings and operational context for real-world use. A chain-aligned audit checklist is provided in Tab. (5). The same sequence of questions and expected evidence is summarized in Fig. (6).

Later stages apply quality assurance gates that screen implausible values, missing data, drift or fouling, and calibration status before alerts are issued, and check that alerts create tasks with assignment and escalation suited to intermittent connectivity. Task follow-through can be summarized by the task closure rate, defined as the number of tasks verified closed divided by the number of assigned tasks, Eq. (3). The resulting definition is shown in

$$ClosureRate = \frac{N_{closed}}{N_{tasks}} \quad (3)$$

Because weighting and threshold choices can change the overall rating, the scoring scheme should be stated and justified explicitly (Pena-Pereira et al., 2020).

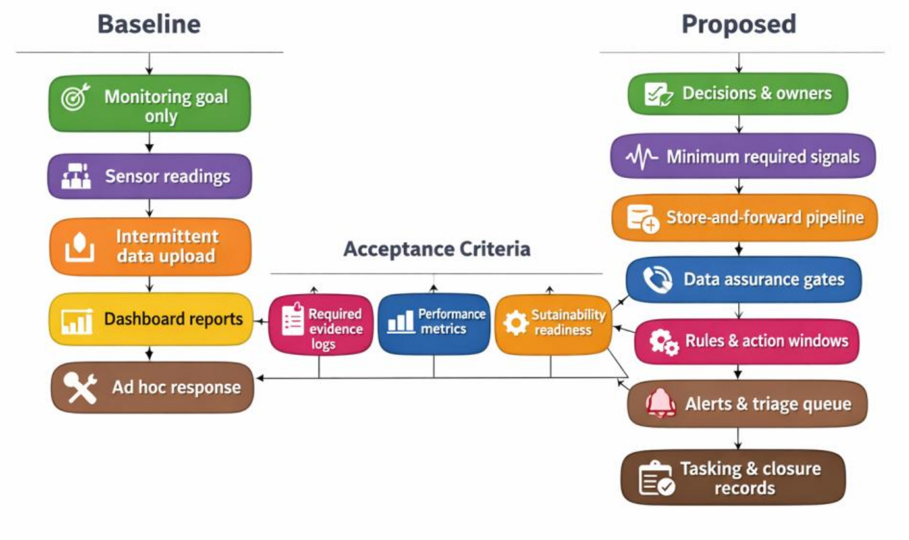

Figure 6. Checklist for true decision support

Table 5. Checklist for true decision support

Chain Stage	*What To Check*	*Evidence To Look For*
Decision And Action Design	Decision archetypes defined with decision owner, action owner, action window, feasible actions, closure evidence	Documented decision archetypes and roles; stated action windows in minutes, hours, days; defined closure or verification status per archetype
Signals And Context Tags	Minimum signals captured: water-quality readings, sensor or system health telemetry, context tags such as asset identity and location	Time-stamped observations linked to asset identity and location; water-quality fields such as turbidity, pH, conductivity, temperature, residual chlorine when treatment is present; health fields such as battery, uptime, connectivity success or failure
Data Assurance Before Alerting	QA and QC gates applied before alerts:	Recorded QA flags per observation; rules or

	plausibility checks, drift or fouling flags, missing-data handling rules, calibration status handling	logs showing plausibility screening and missing-data handling; drift or fouling and calibration status captured and used in alert decisions
Alerts To Tasks and Escalation	Alerts are decision outputs that trigger workflow steps: tiered severity, persistence checks, assignment, escalation, offline use support	Alert payloads with severity; persistence checks to reduce false alerts; task records showing assignment and escalation; support for intermittent-first operation via buffering and store-and-forward
Verification, Closure, And Learning Loop	Response is verified and closed with an audit trail; learning loop updates thresholds and maintenance schedules; monitoring-only is avoided	Closure records with verification status and response time; traceable linkage from alert to action to closure; documented process for updating thresholds and maintenance schedules

Implementing for sustainability in rural programs

Sustainable rural deployment in practical settings depends less on the purchase price of sensors than on maintaining the full data-to-action service over years. Program design should establish **decision chain ownership** by naming a decision owner, an action owner, and a data steward, each with clear authority to acknowledge alerts, dispatch tasks, and record closure evidence. These roles should be supported by routine training and supervision so responsibilities persist despite staff turnover (Lowndes et al., 2017).

Operational capacity should cover the main failure pressures that degrade performance over time, including calibration schedules, drift and fouling checks, and a spares and consumables plan for probes, power components, and connectors given rural transport constraints. Data practices should treat quality assurance as a gate before alerting, with plausibility flags, missing-data handling, and versioned decision rules to reduce avoidable false or missed alerts. **Auditable workflow artifacts** such as alert payloads, task assignments, escalations, and verification records should be updated incrementally using open-source analysis and reporting toolchains (Lowndes et al., 2017; Wessel et al., 2013).

Financing should be planned as recurring operating cost lines that cover connectivity, hosting, calibration supplies, field visits, and time to triage and close cases, rather than a one-off capital line for devices. Procurement and handover packages should include runbooks, configuration records, and local repair pathways so the system can be serviced without external consultants. Routine reviews of alert-to-action linkage and closure rates can guide threshold tuning and workload balancing as conditions change (Lowndes et al., 2017).

Illustrative vignettes mapped to the framework

Three end-to-end vignettes show how near-real-time surveillance links readings to feasible rural actions in practical settings. In a borehole scheme, a turbidity increase is first screened for plausibility, missing data, and likely fouling. Only a persistent signal generates an alert, assigns a pump inspection, and closes after a repeat reading confirms recovery. In a chlorinated supply, low residual chlorine triggers a calibration check and, if repeated, escalates to supervisor review.

In a handpump cluster, abnormal conductivity and pH are triaged across assets using location and the maintenance backlog, while buffered uploads preserve an auditable timeline when messages arrive late. Sensor-health telemetry, including battery and link failures, can suppress water-quality alerts and instead open a maintenance ticket, reducing false tasking. Across vignettes, closure requires a recorded action, verification evidence, and a resolved status rather than a dashboard-only update.

Discussion: trade-offs, generalizability, and next evidence

Design patterns from smart irrigation IoT can help accelerate rural water quality surveillance for real-world use, but their generalizability is limited because agriculture systems usually optimize efficiency under gradual change, whereas drinking water decision support must manage acute health risk under public accountability (Obaideen et al., 2022). This difference shifts the acceptable trade-off between sensitivity and false alerts, increases the need for explicit escalation and closure steps, and places greater value on explainable rules rather than black-box optimization.

In practical settings, a useful framework is to separate components that can be standardized from those that remain context-specific. Standardizable elements include intermittent initial connectivity with buffering, data assurance gates to detect drift, fouling, and missingness, and workflow logs that connect each alert to a task and verification. Context-specific elements include thresholds linked to local sources, the responsible decision owners and budgets, transport and staffing constraints, and the action windows for advisories, maintenance, or shutdown. To support the design of dependable deployments, future field evidence should report data latency, decision latency, response time, closure rates, repeated unconfirmed alerts, and the recurring burden of calibration and repairs, alongside the actions taken and the recorded proof of closure (Obaideen et al., 2022).

Conclusion

This study presents a decision-first framework for IoT-enabled, near-real-time surveillance of rural drinking-water systems that links measurements to named owners, feasible actions, and verified closure, thereby closing the monitoring-to-action gap. For real-world use, it begins with decision archetypes and action windows and then defines the minimum signals, data-assurance gates to detect drift, sensor fouling, and missingness, and tiered alerts that generate tasks, escalation paths, and auditable records. The same structure can audit deployments by testing whether each alert consistently triggers timely action and closure. The contribution is guidance, not evidence of health impact.

References

Alprol, A. E., Mansour, A. T., Ibrahim, E. M., & Ashour, M. (2024). Artificial intelligence technologies revolutionizing wastewater treatment: Current trends and future prospective. Water, 16(2), 314–314. https://doi.org/10.3390/w16020314

Ansari, S., & Vidyarthi, V. K. (2025). Use of internet of things in water resources applications: Challenges and future directions: A critical review. Discover Internet of Things, 5(1). https://doi.org/10.1007/s43926-025-00193-7

Ayaz, M., Uddin, M. A., Sharif, Z., Mansour, A., & Aggoune, E. M. (2019). Internet-of-things (IoT)-based smart agriculture: Toward making the fields talk. IEEE Access, 7, 129551–129583. https://doi.org/10.1109/access.2019.2932609

Elijah, O., Rahman, T. A., Orikumhi, I., Leow, C. Y., & Hindia, M. H. D. N. (2018). An overview of internet of things (IoT) and data analytics in agriculture: Benefits and challenges. IEEE Internet of Things Journal, 5(5), 3758–3773. https://doi.org/10.1109/jiot.2018.2844296

Et-taibi, B., Abid, M. R., Boufounas, E., Morchid, A., Bourhnane, S., Hamed, T. A., & Benhaddou, D. (2024). Enhancing water management in smart agriculture: A cloud and IoT-based smart irrigation system. Results in Engineering, 22, 102283–102283. https://doi.org/10.1016/j.rineng.2024.102283

Gomes, V. C. F., Queiroz, G. R. de, & Ferreira, K. R. (2020). An overview of platforms for big earth observation data management and analysis. Remote Sensing, 12(8), 1253–1253. https://doi.org/10.3390/rs12081253

Govindarajan, P., Shahapuram, V. K., Ganesh, P., Basavalingappa, V. M., Balarama, K. Y., Kumar, S., Cheong, J. Y., & Padil, V. V. T. (2025). Tracking microplastic pathways:

Real-time IoT monitoring for water quality and public health. MethodsX, 15, 103674–103674. https://doi.org/10.1016/j.mex.2025.103674

Lambert, D., & Gilbert, R. O. (1988). Statistical methods for environmental pollution monitoring. Journal of the American Statistical Association, 83(404), 1226–1226. https://doi.org/10.2307/2290180

Leenheer, J. A., & Croué, J. (2003). Peer reviewed: Characterizing aquatic dissolved organic matter. Environmental Science & Technology, 37(1), 18A–26A. https://doi.org/10.1021/es032333c

Lowndes, J. S., Best, B. D., Scarborough, C., Afflerbach, J. C., Frazier, M., O'Hara, C. C., Jiang, N., & Halpern, B. S. (2017). Our path to better science in less time using open data science tools. Nature Ecology & Evolution, 1(6), 160–160. https://doi.org/10.1038/s41559-017-0160

Makumbura, R. K., Mampitiya, L., Rathnayake, N., Meddage, D. P. P., Henna, S., Dang, T. L., Hoshino, Y., & Rathnayake, U. (2024). Advancing water quality assessment and prediction using machine learning models, coupled with explainable artificial intelligence (XAI) techniques like shapley additive explanations (SHAP) for interpreting the black-box nature. Results in Engineering, 23, 102831–102831. https://doi.org/10.1016/j.rineng.2024.102831

Miller, T., Durlik, I., Kostecka, E., Kozlovska, P., Łobodzińska, A., Sokołowska, S., & Nowy, A. (2025). Integrating artificial intelligence agents with the internet of things for enhanced environmental monitoring: Applications in water quality and climate data. Electronics, 14(4), 696–696. https://doi.org/10.3390/electronics14040696

Morchid, A., Alami, R. E., Raezah, A. A., & Sabbar, Y. (2023). Applications of internet of things (IoT) and sensors technology to increase food security and agricultural sustainability: Benefits and challenges. Ain Shams Engineering Journal, 15(3), 102509–102509. https://doi.org/10.1016/j.asej.2023.102509

Morchid, A., Qjidaa, H., Alami, R. E., Mobayen, S., Skruch, P., & Bossoufi, B. (2026). Smart irrigation-based internet of things and cloud computing technologies for sustainable farming. Scientific Reports, 16(1), 5293–5293. https://doi.org/10.1038/s41598-026-35810-0

Obaideen, K., Yousef, B. A. A., AlMallahi, M. N., Tan, Y. C., Mahmoud, M., Jaber, H., & Ramadan, M. (2022). An overview of smart irrigation systems using IoT. Energy Nexus, 7, 100124–100124. https://doi.org/10.1016/j.nexus.2022.100124

Pena-Pereira, F., Wojnowski, W., & Tobiszewski, M. (2020). AGREE—analytical GREEnness metric approach and software. Analytical Chemistry, 92(14), 10076–10082. https://doi.org/10.1021/acs.analchem.0c01887

Popescu, S. M., Mansoor, S., Wani, O. A., Kumar, S. S., Sharma, V., Sharma, A., Arya, V. M., Kirkham, M. B., Hou, D., Bolan, N., & Chung, Y. S. (2024). Artificial intelligence and IoT driven technologies for environmental pollution monitoring and management. Frontiers in Environmental Science, 12. https://doi.org/10.3389/fenvs.2024.1336088

Silva, A. H. M. C. da, SILVA, M. V. D. M. D., Santos, A., & Malagón, L. A. G. (2025). A systematic review for ammonia monitoring systems based on the internet of things. IoT, 6(4), 66–66. https://doi.org/10.3390/iot6040066

Wessel, P., Smith, W. H. F., Scharroo, R., Luís, J., & Wobbe, F. (2013). Generic mapping tools: Improved version released. Eos, 94(45), 409–410. https://doi.org/10.1002/2013eo450001

Yao, K.-M., Habibian, M. T., & O'Melia, C. R. (1971). Water and waste water filtration. Concepts and applications. Environmental Science & Technology, 5(11), 1105–1112. https://doi.org/10.1021/es60058a005