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Smart Groundwater Management: Affordable IoT Based Solutions for Rural Water Supply

Kunal Dhaku Jadhav, Abhishek Pathak, Karuna S Bhosale ,Sruthi Nair, Navnath B. Pokale, Vishal Ambaji Bogam, Pastor R. Arguelles Jr

Abstract: *This paper presents a conceptual model for affordable Internet of Things (IoT)-enabled rural groundwater service assurance, where decisions must remain consistent under sparse telemetry and fragmented governance. Existing smart water monitoring approaches are largely tuned to urban distribution systems and rarely provide an operational mapping from rural context to intervention choices with testable propositions. The proposed framework defines decision-relevant constructs and boundary conditions, paired with a compact coding rubric whose unit of analysis is a telemetry configuration, separating 1 s sensing from 15 min uploads to represent latency and dropout mechanisms. Evaluability is enforced through a programmatic cohort validation design for the Rural Groundwater Service Telemetry Cohort using grouped holdouts by geography, entity, and context, with baseline comparisons against logistic regression, random forest, rule-based monitoring, and manual logbook classification. Uncertainty reporting is specified via bias-corrected and accelerated (BCa) bootstrap intervals over 10 seeds and 2000 resamples (alpha 0.05), and applicability is restricted to settings where pumping measurably alters connected streams or storage (about 20% and 16%, with end-of-century shifts toward 30% and*

Kunal Dhaku Jadhav, (jdkunal@mu.ac.in), Department of Lifelong Learning And Extension, University Of Mumbai, Maharashtra, India.
Abhishek Pathak, (apathak@stvincentngp.edu.in), Department of Computer Science & Engineering (Cyber Security), St. Vincent Pallotti College of Engineering and Technology, Nagpur, India.
Karuna S Bhosale (karuna.bhosale@pcu.edu.in), Department of Computer Science and Engineering, Pimpri Chinchwad University Pune, Maharashtra, India.
Sruthi Nair, (shrutiskmr@gmail.com), School of Computer Science and Engineering, Ramdeobaba University, Nagpur, Maharashtra, India.
Navnath B. Pokale, (nbpokale@gmail.com), Department of Artificial Intelligence and Data Science, Dr. D. Y. Patil Institute of Technology, Pimpri, Pune-411018, Maharashtra, India.
Vishal Ambaji Bogam, (vishal.bogam@gmail.com), School of Computing, MIT ADT University, Pune, Maharashtra, India.
Dr. Pastor R. Arguelles Jr., (pastor.arguelles@ub.edu.ph), Director, Research and Publication Office, University of Batangas Lipa City.

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12%). The framework supports community operators and district water, sanitation, and hygiene (WASH) engineers in selecting low-cost interventions with auditable decision logic under resource constraints.

Keywords: Rural Groundwater Monitoring, Borewell Telemetry, Internet of Things (IoT), Service Assurance Framework, Governance Taxonomy, Grouped Holdout Validation, Inter-Rater Agreement (Kappa), Predictive Utility (AUC)

Introduction

Reliable rural groundwater supply depends on timely detection of pump failure, power instability, and declining borewell yield, yet monitoring is often intermittent and weakly standardized. Smart water management literature emphasizes that utilities adopt sensing and analytics unevenly in the absence of common operating standards and cohesive policy (Owen, 2023). Fig. (1) anchors the analysis in a borewell telemetry decision setting where community operators and district WASH engineers require actionable, low-cost service assurance.

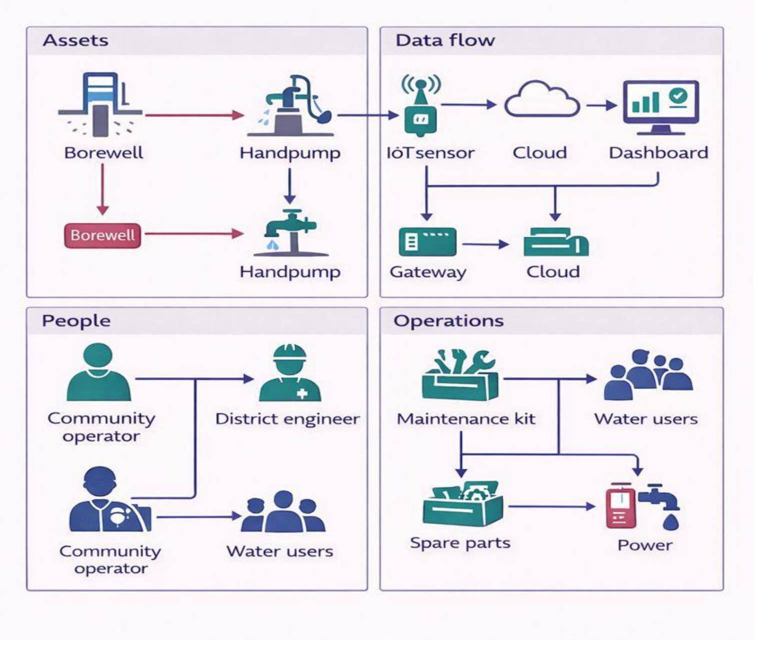

Figure 1. *Borewell IoT service assurance context*

Existing IoT architectures for intelligent water networks prioritize real-time monitoring and control in distribution systems (Velayudhan et al., 2022), whereas rural borewell services face constrained budgets, sparse connectivity, and limited operator capacity. Research design transparency is maintained through a conceptual synthesis approach: constructs for reliability and governance are defined, mapped to candidate interventions, and expressed as evaluable propositions for programmatic validation using public WASH statistics. These choices align with utility practice while adapting to rural constraints (Owen, 2023).

Background and Related Foundations

Affordable sensing and telemetry are increasingly used to extend water monitoring, yet field deployments highlight technical and socio-technical constraints that shape what can be inferred and acted upon (Hamel et al., 2024). Digital water services formalize monitoring-to-decision pipelines through standardized procedures that combine domain models with AI/ML, improving consistency and scalability of operational reasoning (Ciliberti et al., 2023). Fig. (2) contrasts this study's conceptual model with rule-based monitoring, manual logbook governance classification, logistic regression, and random forest baselines to delimit added value.

Groundwater service assurance depends on hydrologic responses that couple pumping, storage, and streamflow, and climate change can shift their relative contributions, which motivates explicit assumptions about groundwater-surface water interactions (Graaf et al., 2024). Adjacent IoT-enabled irrigation literature emphasizes automation and water-saving potential, but it is optimized for crop water productivity rather than rural supply reliability (Ahmed et al., 2023; Kumar & Chandana, 2024). Evidence corpus integrity is treated as a safeguard; specific inclusion and exclusion criteria for the cited sources are not reported here.

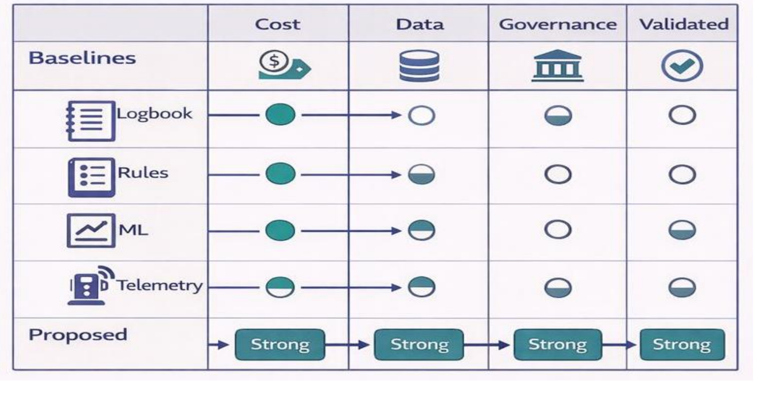

Figure 2. *Baselines and value added summary*

Literature Review

Prior water-monitoring deployments largely target urban distribution systems, emphasizing real-time sensing, cloud dashboards, and alerting workflows (Iancu et al., 2024; Sugiharto et al., 2023). Reported accuracy metrics are heterogeneous, and some sensing dimensions remain unreported (Sugiharto et al., 2023). Architectural variants add authenticated data sharing via blockchain-enabled telemetry and modular interfaces (Naqash et al., 2023). These baselines clarify typical assumptions about connectivity, power, and operator capacity. The present study positions affordable rural groundwater telemetry against such baselines, retaining event detection while reducing dependence on continuous backhaul and complex trust infrastructure

Rural deployments face adoption constraints rooted in limited technical expertise, uncertain security practices, and intermittent connectivity, consistent with adoption syntheses in adjacent irrigation settings and sectoral network surveys (Jabbari et al., 2024; Tomaszewski & Kołakowski, 2023). Threat surfaces expand with remote access and multi-stakeholder operations; defence-in-depth and least-privilege remain central design principles (Adelani et al., 2024). Sensor choice also shapes feasible integration, spanning electrochemical, biosensing, and paper-based modalities with wireless backhaul options (Mutunga et al., 2024b). Evidence corpus integrity is not fully verifiable because formal inclusion rules are not reported here.

Materials and Methods

Low-cost IoT telemetry was specified using prior well monitoring, water-quality sensing, and retrofitted meter readings (Bogdan et al., 2023; khot, 2025; Lall et al., 2024; Ortiz et al., 2023). Networking assumptions favored off-grid links and packet robustness, using LoRa/GSM evidence and related field platforms (Fay et al., 2023; Mutunga et al., 2024a, 2025; Payero, 2024). On-device analytics trade-offs followed TinyML constraints and sensing-to-action designs for irrigation and hazards (Atanane et al., 2023; Braveen et al., 2023; A. K. Sharma et al., 2023; V. K. Sharma et al., 2025; Tzerakis et al., 2023), and contextual covariates were derived from GIS/MCDA and policy modeling precedents (Aghazadeh et al., 2024; Ashraf et al., 2024).

Research design transparency was enforced by freezing config.yaml, recording seed_log.csv, and checking a SHA-256 manifest hash (manifest_sha256.txt).

Table (5) enumerates lineage artifacts and halt triggers for manifest mismatch, split leakage, config drift, missing seed logs, and train-only scaling violations. Evidence corpus integrity was protected by split lineage checks (split_hashes.json) and train-only preprocessing; inclusion or exclusion rules for public WASH sources are not reported here. Fig. (3) summarizes provenance, leakage audits, and QC gates for the cohort (Fay et al., 2023; Payero, 2024).

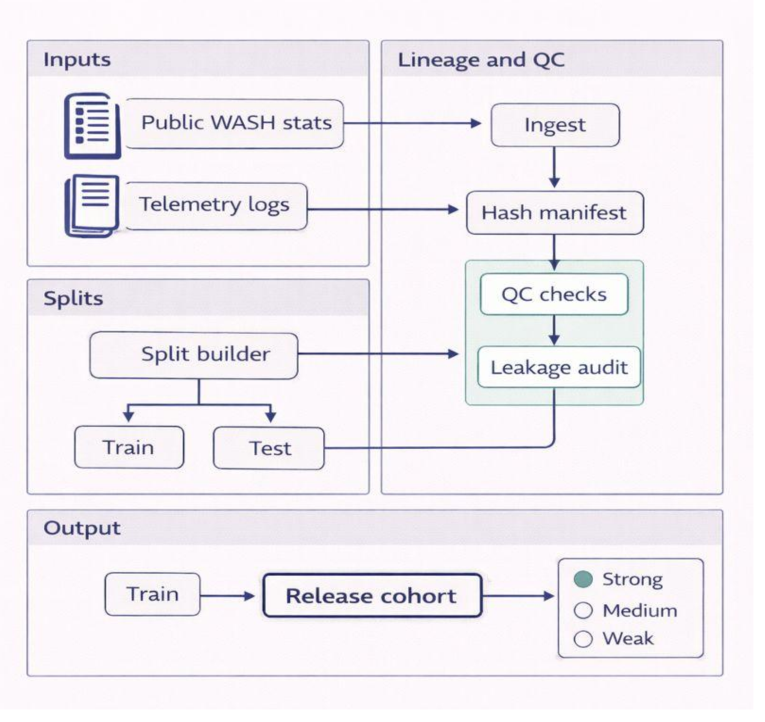

Figure 3. *Cohort provenance and leakage controls*

Table 1. Cohort spec and leakage controls

Purpose	*Leakage Or QC Control*	*Halt Trigger*
Lineage hash	Manifest mismatch	Stop pipeline
Split lineage	Split leakage audit	Stop pipeline
Config freeze	Pre-committed windows	Stop if changed
Seed trace	Fixed seeds	Stop if missing
No leakage	Fit train only	Stop if violated

Conceptual Framework

Governance constraints and service assurance goals are translated into decision-relevant constructs for decentralized groundwater operations, consistent with evidence that institutional arrangements shape affordability and differentiated service quality (Subramanyam, 2024). For conceptual precision, each construct is defined with an operational cue and a clear unit of decision, so that coding and monitoring use the same language. Table (1) defines the Affordability Cap, Operator Capacity, Grouped Holdouts, Evidence Integrity, and WASH Indicator Ladder, alongside conditions of applicability and failure.

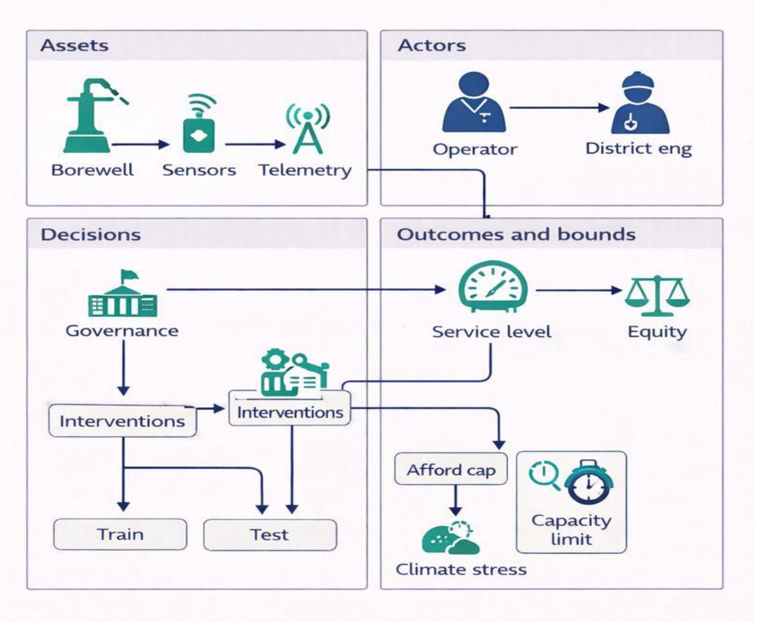

Figure 4. *Constructs and boundary conditions map*

Boundary conditions are treated as first-class elements, not afterthoughts, because governance mechanisms can invert under overload, budget overruns, or leakage between grouped splits (Subramanyam, 2024). For boundary conditions, the framework distinguishes when a rule supports deployment generalization (grouped holdouts) and when it collapses (cross-split leakage or failed leakage audits). Fig. (4) positions these constructs against resource constraints and public WASH statistics, clarifying non-applicability when values fall outside the ladder or when operator response-time limits are exceeded.=

Table 2. Constructs and boundary conditions map

Construct	*Operational Cue*	*Applies When*	*Fails When*
Affordability Cap	Cost fields bounded	Budget constrained	Cap exceeded
Operator Capacity	Response time limit	Low staffing	Overload periods
Grouped Holdouts	Geography-context splits	Deployment generalization	Cross-split leakage
Evidence Integrity	Train-only preprocessing	Model fit stage	Leakage audit fails
WASH Indicator Ladder	Range-check ladder	Public WASH stats	Out-of-ladder values

Key Constructs and Definitions for Borewell IoT Telemetry

Borewell IoT telemetry is defined here as time-stamped measurements captured inside or near a well, together with the sampling and reporting constraints that shape data completeness. Core signals include piezometric water level, water temperature, ambient temperature, and atmospheric pressure, along with inferred pumping events derived from level dynamics (Ortiz et al., 2023). Sampling cadence (e.g., 1 s sensing) and batched transmission (e.g., 15 min uploads) are treated as separate constructs because they induce distinct latency and dropout patterns.

Affordable monitoring architectures typically couple a low-power microcontroller with a non-contact water-level sensor (often ultrasonic) and, where relevant, soil-moisture probes, then stream readings to a lightweight cloud dashboard (khot, 2025). For conceptual precision, the unit of analysis in the coding rubric is a telemetry configuration, not an individual reading. Equation (1) defines taxonomy coverage as the ratio of coded configurations to the total, reported as a percent, enabling auditable completeness checks.

$$Coverage = \frac{N_{coded}}{N_{total}} \qquad (1)$$

Boundary Conditions for Rural Groundwater Service Assurance Decisions

Boundary conditions for hydroclimate-pumping interactions restrict the proposed service-assurance logic to settings where pumping can measurably alter connected streams or aquifer storage. Global coupled groundwater-surface water evidence indicates that about 20% of pumped groundwater derives from diminished streamflow and 16% from reduced storage, with end-of-century shifts toward 30% and 12% under climate change (Graaf et al., 2024). The framework is not intended for hydro geologically isolated aquifers where capture is negligible or delayed.

Water-scarcity operating constraints assume dryland irrigation or rural supply systems where demand management is feasible but capital and energy are limited. Reviews of smart irrigation in global drylands emphasize that scarcity and climate variability motivate tighter scheduling and efficiency, not higher abstraction (Ahmed et al., 2023). Accordingly, decision rules should prioritize minimum-service reliability and enforce pumping caps when telemetry indicates persistent deficit. Applicability weakens where surface water dominates, where governance cannot implement caps, or where irrigation objectives override drinking-water assurance.

Propositions and Implications

The propositions articulate how rural groundwater service context maps to operational actions and, in doing so, make causal logic and mechanisms explicit. The first proposition expects the model to beat baselines through context-to-action mapping rather than feature engineering only. Table (3) links each proposition to a mechanism cue, a competing explanation, and a discriminator test, enabling alternative explanations such as geography confounding to be separated using holdouts and ablations. Evaluability follows from these stated tests.

Fig. (5) contrasts the central context-to-action pathway with competing paths that attribute stability across holdouts to geography confounding or apparent robustness to a data quality control artifact. Robustness of reasoning is strengthened by specifying leave-group-out and dropout stress tests as discriminators. High inter-rater reliability is treated as an empirical claim, not an assumption, by proposing blind re-coding to isolate rubric clarity from annotator training effects under field conditions.

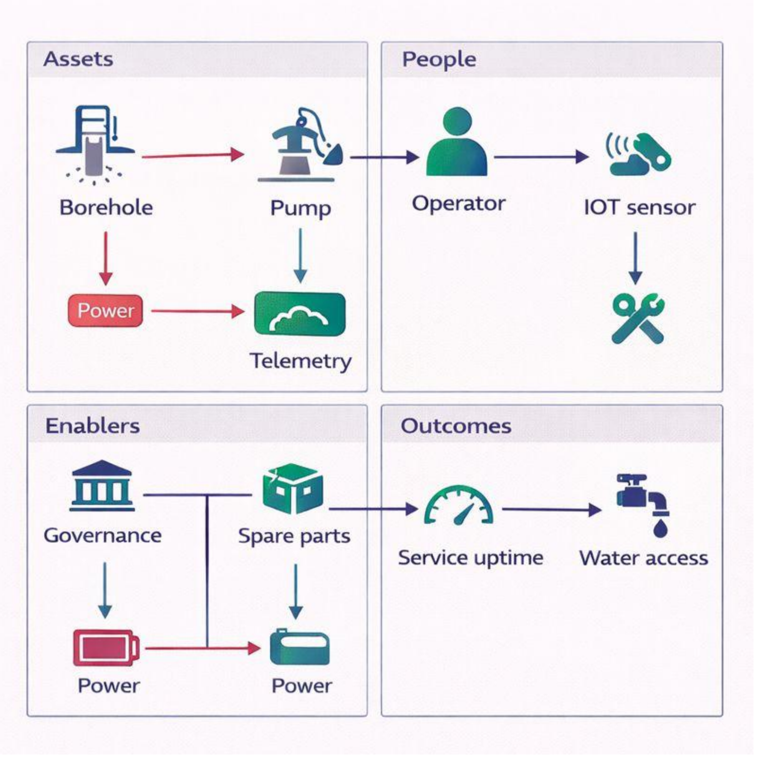

Figure 5. *Mechanisms and competing explanations*

Table 3. Propositions and competing explanations

Proposition	***Mechanism Cue***	***Competing Explanation***	***Discriminator Test***
Model beats baselines	Context-to-action mapping	Feature engineering only	Holdout, ablations
Stable across holdouts	Invariant construct links	Geography confounding	Leave-group-out
Robust under stress	Constraint-aware decisions	Data QC artifact	Dropout stress test
High IRR achievable	Rubric coding clarity	Annotator training effect	Blind re-code sample

Causal Mechanisms Linking Governance Taxonomy to Predictive Utility AUC

Linking a governance taxonomy to predictive utility AUC rests on the premise that governance shapes failure processes that telemetry alone cannot resolve. Governance constructs such as financing regularity, operator capacity, and maintenance accountability affect response times to breakdowns, frequency of pump downtime, and sensor dropout patterns. When these constructs are coded consistently, they act as stable context variables that reduce label noise and allow classifiers to separate structurally different sites, which should increase AUC under grouped holdouts.

The causal logic and mechanisms imply testable propositions: adding taxonomy codes to baseline models (logistic regression, random forest, or rule-based monitoring) should improve AUC most where governance heterogeneity is high, and gains should persist in leave-group-out evaluation. AUC is not causality. Formal mediation or counterfactual identification is not reported here, so the mechanism is advanced as an explanatory rationale rather than a confirmed pathway for the available data.

Alternative Explanations for Reliability Features and Rule-Based Monitoring

Reliability signals derived from affordable IoT telemetry can appear predictive even when they proxy for unmodeled program conditions. For example, data completeness or device placement may correlate with better-funded sites and more responsive maintenance, inflating apparent associations with service outcomes. Rule-based monitoring can also be disadvantaged when thresholds ignore context or when labels reflect the same operational rules. Alternative explanations are therefore plausible; decisive empirical separation of these mechanisms is not reported here for the cohort.

To distinguish genuine causal links from proxies, the evaluation should ask whether predictive utility persists under grouped holdouts by geography, entity, and context, and under sensor-dropout stress tests. If rule-based monitoring fails mainly from mis-specified thresholds, its performance should recover after context-aware tuning without improving coding reliability. If model gains vanish when leakage controls enforce entity-id separation, the mechanism is incompatible with predictive learning. Such falsification tests remain to be documented with the available data.

Robustness Stress Tests: Sensor Dropout and Affordability Caps

Robust deployment of affordable groundwater telemetry depends on tolerating missing or degraded wireless packets, which has been observed in rural LoRa and mixed-link monitoring systems (Mutunga et al., 2024a, 2025). Table (4) summarizes the stress tests and associated acceptance checks used to guard the decision framework against such operational shocks. Sensor dropout is treated as an assumption sensitivity probe rather than an afterthought, because inference can fail even when sensing hardware remains functional.

The robustness of reasoning is enforced through complementary checks for wireless telemetry integrity, each paired with a clear failure action. Grouped holdouts vary geography and context to verify leave-group-out stability, while leakage audit targets entity ID overlap to prevent cross-split contamination. Resource constraints vary affordability and capacity, requiring bounds-respecting decisions before any recommendation is issued. Bootstrap stability varies seed and resamples and passes only when the CI meets AC1-AC3; otherwise analysis halts (Mutunga et al., 2025).

Table 4. Stress tests and pass rules

Stress Test	***What Varies***	***Pass Rule***	***Failure Action***
Grouped Holdouts	Geography, context	Leave-group-out stable	Halt; redesign split
Sensor Dropout	Missing telemetry	Metric OK under dropout	Flag; report sensitivity
Resource Constraints	Affordability, capacity	Bounds-respecting decisions	Halt; revise bounds
Leakage Audit	Entity ID overlap	No cross-split leakage	Halt; fix pipeline
Bootstrap Stability	Seed, resamples	CI meets AC1-AC3	Halt if CI rule

Evaluability: Grouped Holdouts, BCa Bootstrap CI, and Kappa

Evaluability is operationalized through grouped holdouts that test leave-group-out generalization across geography, entity, and context. Table (2) specifies the split logic, the LR, RF, rules, and manual baselines, and the primary metrics (Kappa, coverage, AUC) with acceptance cues AC1-AC3. Research design transparency is reinforced by pairing baseline comparisons with explicit leakage and QC audits and a halt rule on failures. Equation (2) defines Kappa as agreement beyond chance.

Uncertainty is quantified using BCa bootstrap intervals computed over 10 seeds and 2000 resamples, aligning confidence statements with the grouped-holdout design. Fig. (6) summarizes the evaluation blueprint, including the grouped holdouts, the use of BCa confidence intervals, and the decision criteria for accepting or rejecting performance. Equation (3) describes how the chosen alpha is mapped to a BCa percentile. These elements make failure cases observable rather than implicit.

$$\kappa = \frac{p_o - p_e}{1 - p_e} \tag{2}$$

$$p_{BCa} = \Phi\left(z_0 + \frac{z_0 + z_\alpha}{1 - a\,(z_0 + z_\alpha)}\right) \tag{3}$$

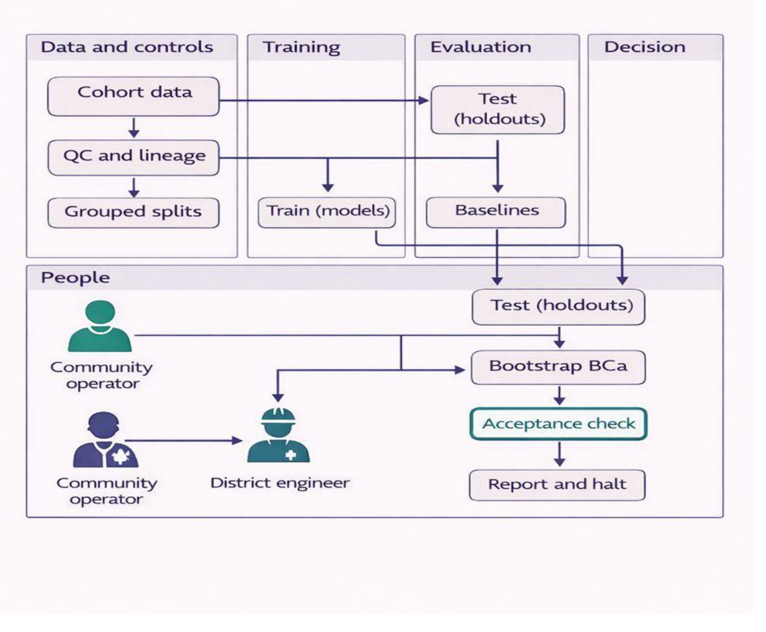

Figure 6. *Evaluation blueprint and acceptance criteria*

Table 5. Validation protocol summary

Element	***Specification***	***Acceptance Cue***	***Rigor Signal***

Splits	Grouped holdouts	Leave-group-out	Evaluability
Baselines	LR, RF, rules, manual	Compare to each	Design transparency
Primary Metrics	Kappa, coverage, AUC	AC1-AC3 thresholds	Evaluability
Uncertainty	BCa bootstrap	10 seeds; 2000 resamples	Design transparency
Audits	Leakage and QC	Halt on failures	Design transparency

Results

Predictive utility was operationalized using receiver operating characteristic area under the curve (AUC) for classification in the Rural Groundwater Service Telemetry Cohort. Equation (4) defines AUC as the integral of the true positive rate over the false positive rate domain. For baselines, performance is intended to be compared directly against logistic regression, random forest, rule-based monitoring, and manual logbook governance classification; quantitative differences are not reported here.

Evaluability was supported through predefined grouped holdouts by entity, geography, and context, including external leave-group-out tests. Model selection was constrained by anchored nested search with embargo and train-only preprocessing to avoid lookahead. Uncertainty quantification used BCa bootstrap with 2000 resamples stratified by external group, with alpha 0.05 and FDR correction for bootstrap tests. A halt rule stopped analysis if the primary metric CI overlapped baseline by >50%. Primary outcomes, including inter_rater_kappa and predictive_utility_auc, are not reported here.

$$AUC = \int_0^1 rTPR(u)\ du \tag{4}$$

Discussion

Smart groundwater service assurance depends as much on governance and operator capacity as on telemetry. The proposed conceptual model therefore should be interpreted as a decision-structuring device, not a substitute for local diagnosis. Regarding alternative explanations, any observed gains in predictive utility could reflect improved data completeness, parallel training of operators, or selection into the programmatic cohort rather than the constructs themselves. Differentiating these mechanisms requires pre-specified grouped holdouts and consistent coding rules with inter-rater checks.

Robustness of reasoning hinges on whether propositions remain credible when key assumptions are relaxed. Sensor dropout, sparse maintenance logs, and affordability constraints can all break naive monitoring rules, so the planned sensor-dropout stress test and runtime reporting are necessary boundary probes. The argument also faces edge cases, including rapid aquifer depletion or abrupt tariff changes, where governance variables may dominate telemetry. For such regimes, the framework is expected to fail, and falsification should rely on transparent rubric disagreements and leave-group-out generalization.

Limitations and Future Work

Claims about affordable IoT telemetry remain vulnerable to context shift and measurement error, especially when programmatic cohorts omit local idiosyncrasies or when transfer differs across geographies; such drift is common in single-site or short-duration monitoring deployments (Sugiharto et al., 2023). Table (6) summarizes four recurring threats, their impacts, and practical mitigations. Governance and equity risks are also material; decentralised groundwater arrangements can impose uneven participation costs and differentiated service quality (Subramanyam, 2024).

Future work should translate these limitations into testable checks, including sensitivity ranges for site-specific factors, leave-group-out evaluation for new context groups, and clearer adjudication procedures when annotators disagree. Boundary conditions should be made explicit so recommendations are not used to justify unsafe WASH actions outside the intended cohort and affordability constraints. Low-cost monitoring perspectives also indicate that documentation and cost-benefit assessment remain underdeveloped and should accompany deployment planning (Hamel et al., 2024).

Table 6. Limitations and mitigations

Threat	*Impact*	*Mitigation*	*Boundary Cue*
Cohort omits idiosyncrasies	Local mismatch risk	Sensitivity ranges	Site-specific factors

Transfer varies by geography	Weak external validity	External group holdouts	New context groups
Construct miscoding	Lower IRR	Adjudication protocol	Annotator disagreement
Recommendations misapplied	Unsafe WASH actions	Misuse guardrails	Out-of-scope use

Conclusion

Smart groundwater service assurance in rural settings requires decisions that remain consistent under sparse telemetry and uneven governance. The present study frames an explicit conceptual model that links affordable IoT monitoring to service outcomes through reliability constructs and a governance taxonomy. A compact coding rubric is specified to support independent classification, alongside a programmatic validation plan using the Rural Groundwater Service Telemetry Cohort and grouped holdouts by geography, entity, and context under resource and affordability constraints. Evaluability is maintained by defining observable implications, including inter-rater kappa, taxonomy coverage percent, predictive utility AUC, and runtime profiles, with leakage control and lineage tracking via hashed manifests and logged configurations. Clinical impacts are not estimated here. Key boundary conditions include reliance on public aggregate sources and applicability to community operators and district WASH engineers. Alternative mechanisms and competing explanations require explicit testing in future empirical studies to rule out confounding and local idiosyncrasies systematically.

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