Comparative Analysis of Gravity-Fed vs. Pump-Driven Rural Water Distribution Models

Varun Kumar Sharma, Vivek Parhate, Gulfsha Parveen, G. Sasikala, Rajesh Raikwar, D. H. Tupe

Abstract: *This paper presents an operational conceptual model for choosing between gravity-fed and pump-driven rural water distribution under affordability limits and constrained operator capacity. Decisions in rural WASH planning are often made with incomplete data and fragmented governance, and practical frameworks that map context to testable decision propositions remain limited. The proposed framework defines the unit of analysis as a candidate scheme within a community context and specifies constructs for life cycle cost (LCC), decision-threshold stability, and service continuity, supported by a coding rubric and explicit causal mechanisms. Evaluability is operationalized using grouped and external holdouts, 4 baseline comparators, 3 primary indicators, and BCa 95% confidence intervals from paired bootstrap with 2000 resamples, alongside stress-test ranges that include demand from 30-650 GPCD and inlet turbidity up to 1863 NTU. Empirical performance outcomes are not reported here; the contribution is a transparent decision model with boundary conditions and misuse guardrails intended to support rural water engineers and planners selecting distribution modalities in resource-constrained programs.*

Keywords: Rural Water Distribution, Gravity-Fed Systems, Pump-Driven Systems, Life Cycle Cost (LCC), Operations and Maintenance Capacity, Grouped Holdout Validation, Service Continuity Modelling, Decision Rubric Coding

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Varun kumar Sharma (varun1.sharma@niu.edu.in), Department of Biotechnology and Microbiology, Noida International University,Greater Noida, Uttar Pradesh, India.
Vivek Parhate (parhatescet@gmail.com), Department of Mechanical Engineering, Suryodaya College of Engineering and Technology, Nagpur, Maharashtra, India.
Gulfsha Parveen (gulfshaparveen@gncdehradun.com), Guru Nanak College of Pharmaceutical Sciences, Dehradun, Uttarakhand, India.
G.Sasikala (sasikala.g@srkrec.ac.in), Assistant Professor,Department of Civil Engineering,S.R.K.R.Engineering College Bhimavaram India
Rajesh Raikwar (rajesh.raikwar@vit.edu), Department of Electrical Engineering, Vishwakarma Institute of Technology, Pune, Maharashtra-411037, India.
D. H. Tupe (durgeshtupe@gmail.com), Associate Professor, Deogiri Institute of Engineering and Management Studies, Chhatrapati Sambhajinagar, Dr. BATU University, Lonere, Maharashtra, India

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Introduction

Rural WASH planning often requires choosing between gravity-fed and pump-driven distribution under affordability limits and constrained operator capacity. Energy insecurity can make pump-dependent service brittle, as disruptions in scheduled delivery have been documented in rural settings (Machimana et al., 2024). Fig. (1) situates the decision setting around pumps, storage tanks, piping, telemetry, and a checklist cue. The present study targets an operational conceptual model that links context to these intervention choices.

Research design transparency is addressed by combining theory synthesis with an explicit validation plan: constructs are defined for rubric-based coding, propositions are stated as observable implications for service outcomes, and evaluation rules emphasize grouped and external holdouts. The benchmarking protocol aligns with prior work that highlights energy-water trade-offs and infrastructure siting constraints (Karambelkar et al., 2025; Machimana et al., 2024). Key limitations include incomplete representation of local idiosyncrasies and potential misapplication outside stated boundary conditions.

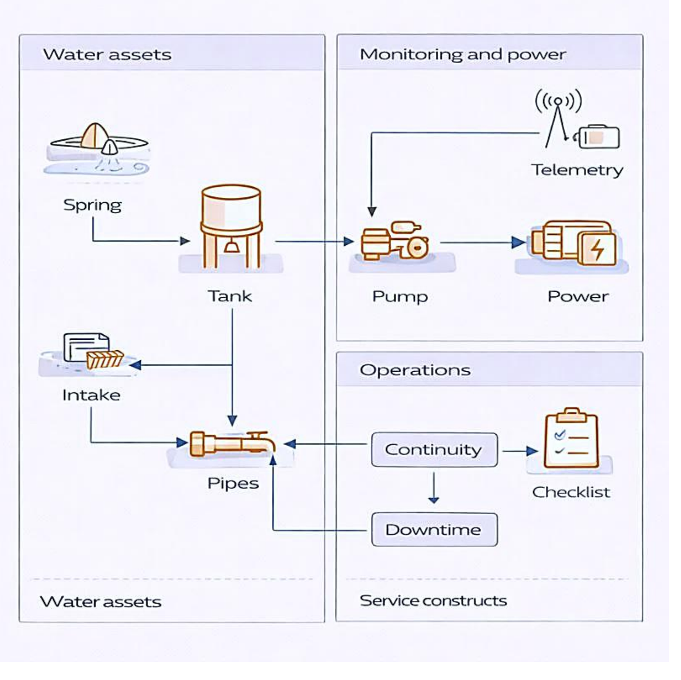

Figure 1. *Rural WASH decision context scene*

Background and Related Foundations

Rural water distribution choices between gravity-fed and pump-driven schemes are typically constrained by scarcity dynamics and operational intermittency. Monthly sub-basin scarcity assessments quantify where and when demand exceeds blue-water availability, motivating context-specific service targets (Deng et al., 2025). Related optimization work on intermittent supply operations frames the trade-offs among reliability, resource limits, and objectives, informing the present benchmark protocol (Ayyash et al., 2024). These foundations justify treating context and operating constraints as first-order determinants of feasible design options.

Conceptually, the proposed framework draws on integrated accounts that link human behavior, leadership, economic incentives, and technology in water crisis management (Yasmeen et al., 2024), alongside Water-Energy-Food nexus modeling that treats energy availability and cooperation as coupled drivers of water service options (Lodge et al., 2024). Baselines are specified to anchor claims in familiar decision rules, including a decision tree surrogate, regularized regression surrogate, capex-only comparison, and a pump-availability rule-of-thumb. Evidence corpus integrity remains bounded by what was assembled; explicit inclusion and exclusion rules are not reported here.

Literature Review

Prior hydrological modeling provides context for resource availability and demand that can condition rural distribution choices. WaterGAP v2.2e formalizes naturalized water resource and use accounting with calibration against extensive streamflow observations, offering reproducible inputs for scenario-based planning (Schmied et al., 2024). Agent-augmented large-scale models further illustrate how behavioral adaptation can shift shortage outcomes, highlighting the importance of endogenous responses when evaluating intervention feasibility (Yoon et al., 2024). These strands motivate a context-linked scheme selection model rather than a purely hydraulic comparison.

System dynamics studies offer complementary structure for mapping policy levers to service outcomes under uncertainty. Basin-scale analyses have tested demand-side strategies across climate and socio-economic scenarios and reported model accuracy in terms of mean absolute error (MAE), while noting that economic feasibility can alter conclusions (Baharanchi et al., 2024). Disaggregated water-food-energy simulations extend this logic via Monte Carlo sensitivity to compare integrated policy bundles (Zahedi et al., 2024). The benchmark protocol therefore follows scenario- and sensitivity-driven evaluation patterns established in this literature.

Selection and Provenance of WASH Evidence Corpus and Utility KPIs

The WASH evidence corpus was assembled from public, aggregate programmatic statistics to support comparisons between gravity-fed and pump-driven rural schemes. Evidence corpus integrity was maintained through explicit inclusion and exclusion rules and documented provenance checks. Fig. (2) traces the screening and lineage steps used to construct the corpus and derive KPI proxies. Public-supply water statistics, as in (Alzraiee et al., 2024), motivated treating inputs as aggregate cues rather than site measurements.

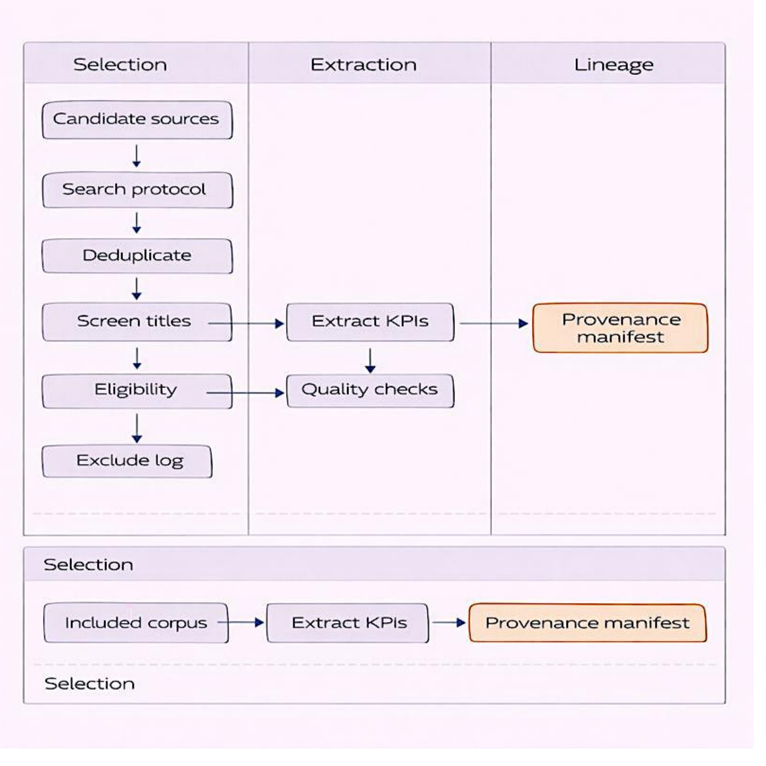

Figure 2. *Evidence corpus selection and provenance*

Table (1) summarizes corpus sources, applied controls, and KPI definitions. For evidence corpus integrity, key controls include train-only fitting, no lookahead, cross-split leakage checks, hash-verified manifests with mismatch halts, and range validation. The resulting KPIs include decision consistency, Model calibration MAE, holdout stability, auditability KPI, and continuity MAE, consistent with reproducibility-oriented dataset reporting (Mialyk et al., 2024). Baselines include a capex-only comparison, a pump-availability rule-of-thumb, and surrogate decision tree and regularized regression models.

Table 1. Corpus provenance and KPI mapping

Corpus Element	***Provenance Cue***	***Filter Or Control***	***KPI Or Proxy***
Programmatic cohort	Public WASH stats	Public aggregate only	Decision consistency
Preprocessing	Train-only fit	No lookahead	Model calibration MAE
Splitting scheme	Entity and context	No cross-split leakage	Holdout stability
Lineage logging	Hashed manifests	Hash mismatch halt	Auditability KPI
Range validation	Published ladders	Range checks	Continuity MAE

Baseline Decision Approaches for Gravity-Fed vs Pump-Driven Schemes

Baseline decision approaches for choosing gravity-fed versus pump-driven schemes typically reduce the problem to a small set of heuristics or single-criterion practical comparisons. Benchmarking therefore draws on established cost-accounting and scenario-based evaluation traditions in water planning, which quantify cost drivers under varying conditions and test policy sensitivity to behavioral heterogeneity (Verlicchi et al., 2024; Vidal-Lamolla et al., 2024). Fig. (3) contrasts these baselines with the proposed model, clarifying the decision information each baseline omits.

The present study treats baselines as intentional simplifications: capex-only ranking, a pump-availability rule-of-thumb, and statistical surrogates such as decision trees and regularized regression. Related resource-allocation models and simulation-optimization frameworks show how scenario structure and uncertainty handling can alter preferred actions, even with limited data (Sawassi et al., 2024;

Zhao et al., 2024). The proposed model adds explicit context-to-choice propositions and evaluable indicators (for example, model calibration mae cost, threshold stability percent) under grouped and external holdouts. This shift enables comparison beyond cost, including continuity prediction mae and stress tests for energy price and downtime.

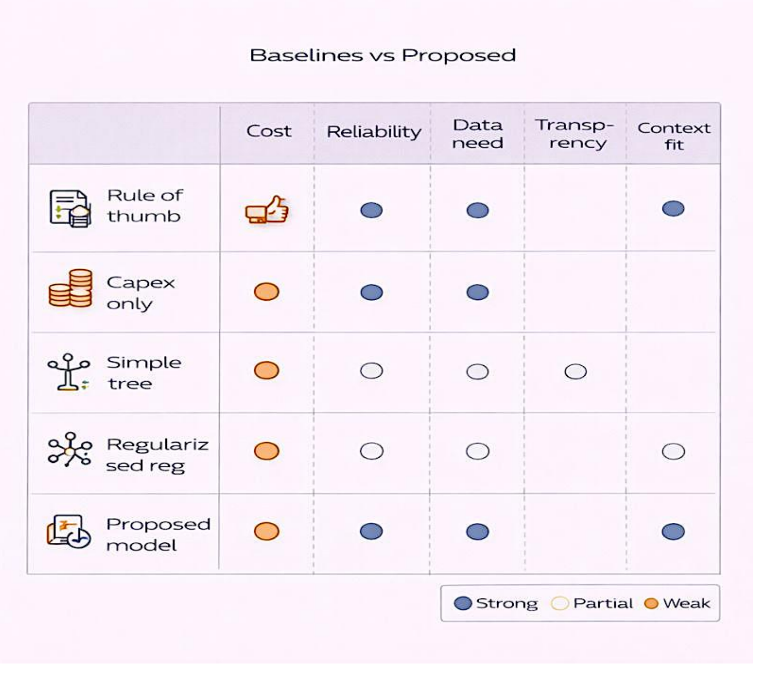

Figure 3. *Baseline decision approaches comparison*

Conceptual Framework

The conceptual framework links rural context conditions to the selection of gravity-fed or pump-driven distribution schemes and to expected service performance. The unit of analysis is a candidate scheme within a community context, encoded as technical feasibility, affordability constraints, and operator capacity. Core outcomes are expressed as calibrated cost predictions, decision-threshold stability, and continuity predictions. This structure separates intervention choice from outcome measurement to support transparent comparison across settings.

Mechanistically, gravity-fed schemes are expected to benefit from low recurring energy needs, while pump-driven schemes depend more strongly on energy price and downtime exposure, which can erode continuity. The framework treats these links as propositions that can be tested using grouped and external holdouts, with preprocessing fitted on training data only and leakage audits. Sensitivity analyses and stress tests probe assumption robustness; competing explanations are not elaborated here.

Key Constructs and Definitions for Life Cycle Cost and Reliability

Core constructs are specified to support consistent coding of life cycle cost (LCC) and reliability in rural water scheme comparisons. For conceptual precision, Fig. (4) maps each construct to its unit, measurement source, and intended use in the benchmark protocol aligned with prior operational water-use analytics (Marsili et al., 2024; Mazzoni et al., 2024). Table (2) formalizes the coding rubric for model calibration mae cost (USD per m3), threshold stability percent (Percent), and continuity prediction mae (Hours). Grouped holdouts are recorded as group splits to prevent cross-group leakage.

Equation (1) defines discounted LCC as capital expenditure plus discounted operating, energy, and repair costs over a horizon T at discount rate r. Equation (2) defines availability as MTBF divided by MTBF plus MTTR, linking failure and repair dynamics to expected service continuity. Reporting follows the operational definitions used for construct coding (Ogunbode et al., 2024), so that calibration error, threshold stability, and outage prediction error remain comparable across gravity-fed and pump-driven schemes.

$$LCC = C_{capex} + \sum_{t=1}^{T} \frac{C_{om,t} + C_{energy,t} + C_{repair,t}}{(1+r)^t} \tag{1}$$

$$Availability = \frac{MTBF}{MTBF + MTTR} \tag{2}$$

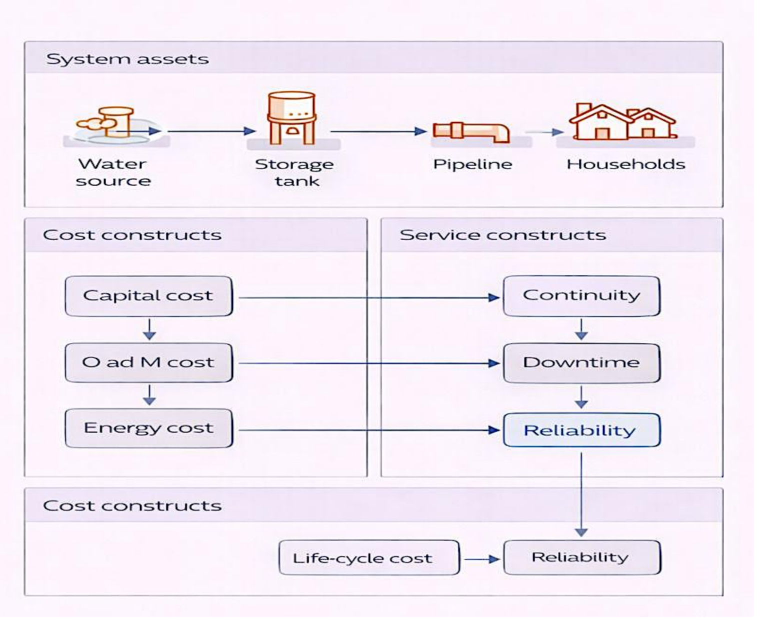

Figure 4. *Key constructs and definitions*

Table 2. Construct definitions and units

Construct	***Unit Or Scale***	***Operational Definition***	***Coding Guidance***
Model Calibration MAE Cost	USD per m3	Mean absolute error	Lower is better
Threshold Stability Percent	Percent	Stable threshold share	Higher is better
Continuity Prediction MAE	Hours	Outage prediction error	Lower is better
Grouped Holdouts	Group split	External group holdout	No cross-group leakage

Boundary Conditions: Terrain, Demand, Affordability, and O and M Capacity

Boundary conditions are operationalized as context-defined applicability zones for terrain, demand, affordability, and O and M capacity, with subgroup definitions adapted from prior stakeholder and adoption typologies (Kimbowa et al., 2025; Tolessa, 2024). Fig. (5) delineates where gravity-fed or pump-driven schemes are expected to be feasible and where misapplication risks are highest. Table (3) specifies stress-test ranges, including demand from 30-650 GPCD and inlet turbidity up to 1863 NTU. Additional cues cover load-shedding disruption and peak-month scarcity.

Affordability is treated as a hard constraint rather than a preference: Equation (3) encodes whether life-cycle cost (LCC) remains below an explicit maximum (C_max). The framework is not intended for settings in which prolonged resource deficits, policy shocks, or governance failures dominate service outcomes, because these dynamics can decouple infrastructure choice from observed reliability (Boeing et al., 2024; Visser et al., 2024). Boundary conditions therefore include non-applicability zones when O and M response capacity or energy reliability cannot sustain pumping continuity.

$$AffordabilityOK = 1\{LCC \leq C_{max}\} \tag{3}$$

Figure 5. *Applicability zones and boundaries*

Table 3. Boundary conditions and ranges

Boundary	***Range Or setting***	***Stress Test Cue***
Energy Reliability	Load-shedding downtime	Pumping disruption (Machimana et al., 2024)
Demand Level	Per-capita use span	30-650 GPCD (Alzraiee et al., 2024)
Water Scarcity	Peak-month scarcity	Unsustainable demand (Deng et al., 2025)
Treatment Quality	High turbidity inlet	Up to 1863 NTU (Verlicchi et al., 2024)

Propositions and Implications

Propositions link rural context to the comparative suitability of gravity-fed and pump-driven distribution schemes through affordability, operator capacity, and energy dependence. Where elevation head is available and energy prices are volatile, gravity-fed schemes are expected to reduce cost variance and improve continuity relative to pump-driven schemes. Where source levels fluctuate or distribution must be actively regulated, pump-driven schemes may better maintain service but at higher exposure to downtime and tariff shocks under typical rural maintenance constraints.

These propositions remain evaluable because constructs are mapped to observable indicators, including model calibration mae cost, threshold stability_ percent, and continuity prediction mae, and are benchmarked against decision tree surrogate, regularized regression surrogate, capex-only comparison, and pump-availability rule-of-thumb. Validation is intended to rely on grouped and external holdouts with leakage audits, with uncertainty quantified by bootstrap intervals and paired tests. Alternative explanations and case-selection rules are not reported here, which limits interpretability. Sensitivity analyses for energy price and downtime provide partial robustness checks.

Causal Mechanisms Linking Energy Downtime and Continuity Prediction MAE

Continuity prediction MAE is expected to worsen when energy downtime increases, because supply interruptions directly distort observed continuity signals and degrade model generalization across contexts. Table (4) summarizes the causal logic and mechanisms by pairing each pathway with its key assumption and expected sign. Gravity Head Advantage implies that sufficient elevation head lowers energy dependence, which should improve continuity. By contrast, Pumping Energy Exposure links grid and fuel volatility to higher downtime risk and worse continuity (Hazimeh & Jaafar, 2024).

The remaining pathways specify how constraints translate into longer outages and, in turn, larger continuity_prediction_mae under grouped holdouts. Operator Capacity Constraint assumes limited O and M staff, so repairs lag and outages persist. Affordability Cap Binding posits tariff and budget limits that defer maintenance and reduce reliability. Governance Feature Effect requires institutions to be measurable in the cohort, so better decisions plausibly reduce model_calibration_mae_cost; this assumption should be scrutinized, consistent with sensitivity to upstream model choices in (Hazimeh & Jaafar, 2024).

Table 4. Causal mechanisms and expected signs

Mechanism	*Key Assumption*	*Expected Effect*	*Outcome Cue*
Gravity Head Advantage	Sufficient elevation head	Lower energy dependence	Better continuity
Pumping Energy Exposure	Grid and fuel volatility	Higher downtime risk	Worse continuity
Operator Capacity Constraint	Limited O and M staff	Slower repairs	Longer outages
Affordability Cap Binding	Tariff and budget limits	Deferred maintenance	Lower reliability
Governance Feature Effect	Institutions measurable in data	Better decisions	Lower cost MAE

Alternative Explanations: Governance Features and Capex-Only Comparisons

Capex-only comparisons can misattribute scheme performance when governance and user behavior shape realized service levels. Regarding alternative explanations, observed advantages of gravity-fed or pump-driven options may reflect differences in rule enforcement, tariff compliance, or institutional legitimacy rather than hydraulics alone. Survey evidence indicates that acceptance of formal water management systems varies with socioeconomic attributes and existing irrigation practices (Morepje et al., 2024), implying that similar infrastructure can yield different outcomes across communities.

A second competing mechanism is that irrigation access and farm income conditions may drive welfare-linked endpoints, obscuring attribution to distribution modality. In district-level comparisons, irrigators reported materially higher food security and production than non-irrigators, in association with household size and income (Mupaso et al., 2024). Distinguishing these mechanisms would require governance and livelihood covariates in the proposed rubric and holdout analyses; such evidence is not reported here and would clarify when capex-only baselines are misleading.

Evaluability: Grouped Holdouts, Bootstrap CI, and Decision Rules

Evaluability was operationalized through a pre-specified validation blueprint that couples grouped holdouts with explicit decision rules for model acceptance. Fig. (6) outlines the grouped holdout structure, bootstrap uncertainty reporting, baseline comparisons, and acceptance decision rules used to keep the framework evaluable. Research design transparency is strengthened by fixing the split logic to prevent leakage across entities and contexts, and by committing to a stable baseline set for comparison.

Equation (4) defines mean absolute error (MAE) as the average absolute deviation between predicted and observed values for each metric. Table (5) specifies grouped holdouts, 4 comparators, 3 primary metrics, and BCa 95% CI estimation via paired bootstrap with 2000 resamples and FDR correction. Evaluability is reinforced by linking acceptance cues (AC1-AC3) to these metrics, while robustness checks (ablations and stress tests) are planned with Seeds=10. Empirical outcomes are not reported here.

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|\hat{y}_i - y_i| \tag{4}$$

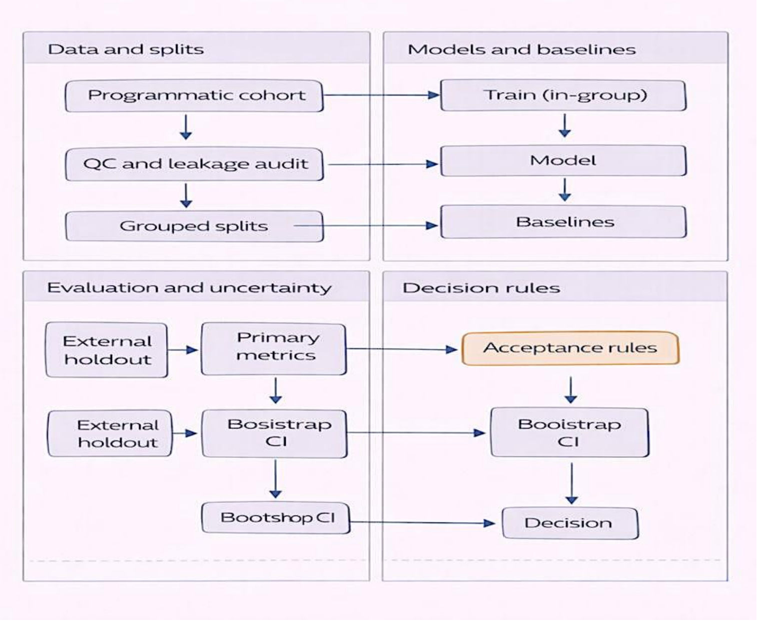

Figure 6. *Validation blueprint and decision rules*

Table 5. Validation protocol summary

Element	*Specification*	*Acceptance Cue*	*Uncertainty*
Splits	Grouped holdouts	No leakage	External group stratify
Baselines	4 comparators	Beat baseline	Baseline set fixed
Primary Metrics	3 MAEs or %	Meet AC1-AC3	BCa 95% CI
Statistical Test	Paired bootstrap	FDR corrected	2000 resamples
Robustness Checks	Ablations, stress tests	H2 support	Seeds=10

Limitations and Future Work

Key limitations arise from the programmatic cohort and from transfer across settings, which can constrain how confidently gravity-fed and pump-driven choices generalize. Table (6) summarizes four recurring threats, their expected impacts, and the mitigations used to bound interpretation. Cohort gaps may miss local idiosyncrasies, a concern consistent with climate- and region-dependent water assessments reported in related footprint analyses (Demeke et al., 2024; Sharafi et al., 2024). These limitations define where conclusions should be treated as provisional rather than prescriptive.

Robustness of reasoning is strengthened by sensitivity ranges, external holdouts for geography shift, and rubric quality controls based on inter-rater reliability plus adjudication, but the magnitude of residual bias is not reported here. Misuse guardrails remain necessary when translating results into guidance. Future work should expand the cohort to additional geographies and operator-capacity regimes, and formalize competing mechanisms that may explain scheme choice. Benchmark designs can draw on probabilistic scenario analysis and dynamic shock modeling used in adjacent water-systems studies (Elzaki & Al-Mahish, 2024; Zhang et al., 2024).

Table 6. Limitations and mitigations

Limitation	*Impact*	*Mitigation*	*Boundary Cue*
Programmatic cohort gaps	Local context miss	Sensitivity ranges	Local idiosyncrasies
New geography transfer	Generalization drift	External holdouts	Geography shift
Rubric miscoding	Measurement bias	IRR plus adjudication	Coder disagreement
Policy misuse risk	Unsafe guidance	Misuse guardrails	Out of scope

Conclusion

This study develops a conceptual basis for choosing gravity-fed or pump-driven rural water distribution schemes under affordability and operator-capacity constraints. The proposed model links contextual drivers to intervention choices and to observable service outcomes, enabling structured comparison beyond capex-only judgments. A coding rubric is specified to support consistent construct annotation by independent reviewers. A validation blueprint is outlined using grouped and external holdouts, calibration and continuity errors, and threshold stability, with comparisons to surrogate and rule-of-thumb baselines.

The framework is intended for programmatic planning and policy guidance rather than site-specific engineering designs or procurement specifications. Its applicability may weaken where local hydrology, governance, or tariff regimes deviate from the cohort assumptions, and transfer across geographies remains uncertain despite external holdouts. Construct mis-coding is a practical risk and requires adjudication. Alternative mechanisms, such as political economy constraints or demand shifts, are not developed here, and empirical performance results are not reported. Planned sensitivity and stress tests can partially probe these uncertainties.

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