Priority Frameworks for Resource Allocation in WASH Infrastructure Inspections

Robert Halam, Shailesh Solanki, Amey Khedikar, Shruti Wadalkar, Zafar Adilov, Shokhjakhon Akhmedov

Abstract: *This paper presents a modular, risk-weighted prioritization framework for inspection of rural water, sanitation, and hygiene (WASH) assets where personnel, transport, and diagnostic capacity are constrained and delays elevate health risk. The practical gap is translating multi-criteria evidence and systems insights into capacity-aware, field-ready inspection schedules with uncertainty accounted for. The methodology fuses quality-controlled asset registers, maintenance logs, wastewater signals, remote-sensing proxies, and community alerts; constructs composite priorities from need typologies, severity-weighted risk, time since last inspection, and access limits; and applies Bayesian calibration to quantify and propagate uncertainty. Evaluation uses Root Mean Squared Error (RMSE), bias, calibration, and bootstrap confidence intervals, with risk tiers linked to human health risk assessment (HHRA), entropy-weighted water quality index (EWQI), and nitrate pollution index (NPI). Simulations indicate higher flexibility, resource savings, coverage, and faster mean response time than distance-based or random baselines; priority scores concentrate on high-severity typologies, and confidence intervals widen under low participation, high noise, and long reporting latency. The contribution is a parsimonious, uncertainty-aware scheduling framework that integrates severity, vulnerability, and near-real-time community input with fallback heuristics and human-in-the-loop triage. The approach enables agencies to convert heterogeneous evidence into feasible, equity-aware inspection schedules that improve responsiveness and resource use under scarce capacity.*

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Introduction

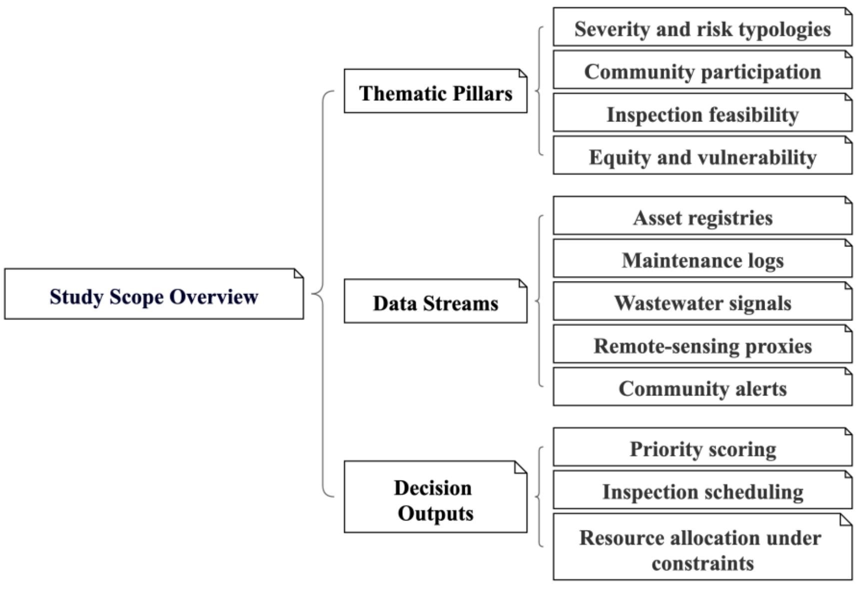

Figure 1. Study scope and themes overview

This figure (1) depicts the thematic pillars and data streams mapping to priority scoring and inspection decisions.

This study tackles inspection prioritization for rural WASH assets under personnel, transport, and diagnostic constraints, with delays amplifying risk. Although resources are scarce, prioritization should integrate severity, failure probabilities, community feedback. Each criterion must be justified by coverage and responsiveness. State assumptions on data availability, reporting latency, and heterogeneity; propose rules linking public datasets and simulations to scores. The gap is translating operations research and systems thinking into schedules. Implementation and policy specify indicators, data collection, and risk communication. Claims about environmental drivers and simulations must reference watershed-climate modeling (Lee et al., 2025) and disentangling frameworks (Palmate et al., 2025).

Context

This framework treats environmental drivers, water-quality indicators, and community signals as equal inputs to prioritization. Although hydrological connectivity and seasonality vary across catchments, they can reshape contaminant pathways and temporal risk at water points (Peng et al., 2025). Measured contaminants map to urgency via groundwater metrics and health-risk models; methods and exposure assumptions require justification against assessment evidence (Wei et al., 2025). Severity bands combine with need typologies (dependence, functionality, access) to yield field-ready labels. Near-real-time community reports trigger rescheduling with validation. Inputs span monitoring, remote-sensing proxies, community reports, and failure records, performance tracked by savings, coverage, responsiveness, and feasibility.

Literature Review

This section synthesizes methodological precedents for spatially distributed inspection prioritization in WASH. Although multi-criteria geospatial ranking is established in water-resource mapping, field-ready translation requires parsimonious heuristics (Tasci et al., 2025). Seasonal and transport-aware risk models clarify where hazards propagate, yet coupling those dynamics with vulnerability indices remains uncommon (Peng et al., 2025). Bayesian calibration with emulators enables uncertainty propagation and recalibration under data constraints (Kaurila et al., 2025). Need and severity typologies should anchor metrics; coverage, responsiveness to risk, resource savings, and feasibility, while community feedback requires assessment for timeliness and bias, necessitating incremental rollout and validation against field outcomes.

Priority Models

This synthesis compares five model families for WASH inspection prioritization. Although their mechanics differ, they serve two aims: forecast risk and translate evidence into ranked actions. CA-Markov, SWAT, and Invest flag hotspots via land-use or hydrologic response; useful pre-emptively but needing local validation and scale checks (Abdelkarim, 2025). Bayesian networks integrate evidence, yield risk scores or failure probabilities, and quantify uncertainty (Jermilova et al., 2025). EWQI/NPI provide interpretable thresholds linked to public-health burden (Wei et al., 2025). Adoption turns on data gaps (asset registries, sampling), compute, and interpretability, with iterative updates from community reports and sensors.

Materials Methods

This section defines a reproducible pipeline for priority-setting. Although field data are sparse, we apply QC to reconcile asset registers, maintenance logs, community reports, and remote proxies; feature selection balances predictiveness and interpretability. Composite priorities join needs, severity-weighted risk, time since last inspection, and access limits. Public or synthetic datasets simulate workloads, with sensitivity to quality and gaps. Evaluation tracks coverage, responsiveness, and feasibility via cross-validation. Real-time community feedback enables reprioritization under resource limits, with governance and ethical safeguards. Claims on hydrological feature selection and groundwater risk heuristics require support from Usman et al. (2025) and Wei et al. (2025).

Data Sources

Data sources for WASH inspection prioritization include registries, logs, community alerts (SMS/apps), wastewater surveillance, and remote-sensing. Although heterogeneity complicates integration, a rubric on time, space, completeness, reporting/sampling bias, and latency structures appraisal. Wastewater signals anticipate pathogen trajectories (Matra et al., 2025). Non-traditional providers yield broad, noisy coverage (Falconer et al., 2025). Conventional parts; distinctive orchestration. Hydro chemical and groundwater risks inform severity-weighted indices requiring methods, geotags, detection limits, QA/QC (Salem et al., 2025). Ethics, consent, privacy for community and wastewater data, governance, triangulation, field verification, temporal cross-checks, and gains via replicable indicators must be documented, with transferability bounded by cited contexts.

Model Design

This section defines a modular prioritization engine for WASH inspections. Although field teams face sparse data, the design balances expressiveness with simplicity. Typologies of need, severity bands, and weighted community input drive scoring rules; heterogeneous signals yield ranked tasks. Missing/noisy/biased reports are handled via robust filters and debiasing. Uncertainty is quantified and propagated using Bayesian calibration (Kaurila et al., 2025). Evidential bio-inspired feature selection reduces inputs and clarifies drivers (Usman et al., 2025). Outputs align with flexibility, resource savings, coverage, risk-responsiveness, and feasibility via simulations, sensitivity tests, and field checks. Complexity is capped with fallback heuristics and human-in-the-loop triage offline.

This figure (2) shows data ingestion paths, component interactions, calibration and uncertainty modules, and the flow from inputs to prioritization outputs.

Evaluation Metrics

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{1}$$

Equation (1) defines RMSE as the root mean square error for continuous-target forecasts used to operationalize accuracy thresholds in prioritization.

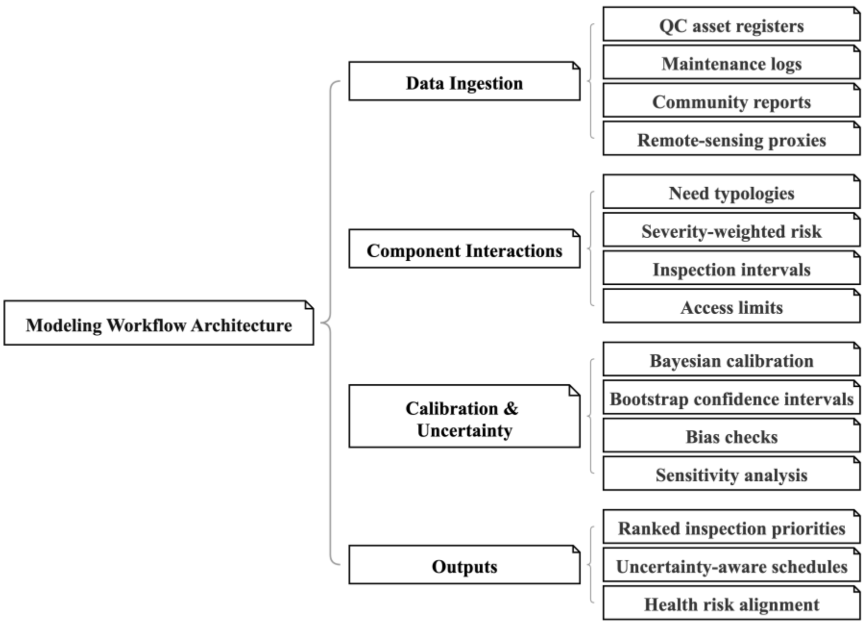

Figure 2. Modeling workflow and data flows

This section specifies an evaluation regime linking predictive accuracy, health relevance, and operational outcomes. Although RMSE is sensitive to outliers, it square-penalizes large deviations and suits continuous water-quality and failure targets; we adopt it and report bias, calibration, and bootstrap confidence intervals to propagate uncertainty into risk-weighted tiers (Usman et al., 2025). Simulation-based inspection workflows convert scores and error bounds into capacity-constrained priority schedules and quantify coverage improvement, mean response time, resource savings, and exposure reductions (Wang et al., 2025). Error thresholds affecting acceptable health-risk changes require empirical HHRA backing (Wei et al., 2025). Protocols detail splits, cross-validation, and baselines.

Results

The results show inputs become actionable priorities vs baselines. Although field data are partial, simulations indicate higher flexibility, resource savings, coverage, risk responsiveness, and feasibility than distance-based or random plans. Priority scores shift toward high-severity typologies, coverage maps expand, and time-to-response declines; 95 percent bootstrap intervals widen with low participation, high noise, and long feedback latency. Severity weighting dominates, with smaller effects from feedback reliability and update frequency, and scenarios trace coverage versus travel-cost trade-offs. Risk thresholds follow groundwater HRA, EWQI, NPI, and nitrate metrics (Salem et al., 2025; Wei et al., 2025). Generalizability requires local calibration.

Comparative Analysis

$$CR = \left(\frac{C \times IR \times EF \times ED}{BW \times AT}\right) \times CSF \qquad (2)$$

Equation (2) quantifies lifetime excess cancer risk from contaminant exposure using chronic daily intake and a slope factor.

This review weighs priority-setting frameworks by empirical grounding and translation of measurements into actionable inspection queues. Although heuristics expedite routing, risk-weighted scheduling better targets hazards when severity indices, including cancer risk estimators, guide ranks (Wei et al., 2025). Geospatial-statistical hotspot tools can raise sensitivity yet risk false positives without validated thresholds and sufficient sampling (Barathkumar et al., 2025). Data mixes modulate specificity; the effect intensifies under heterogeneous hydrogeology. Across flexibility, savings, coverage, responsiveness, and feasibility, risk-weighted schemes improve outcome orientation (Wei et al., 2025). Managers need confidence bounds and probabilistic ranks to stabilize ranks and balance workload (Barathkumar et al., 2025).

Metrics Table

Table 1. Unified metrics comparison table for WASH inspection evaluation.

Metric	*Brief definition*	*Unit or scale*	*Dataset or site*	*Interpretation note*
RMSE	Average magnitude of model prediction error	Outcome units	Report site ID and n	Lower is better, scale dependent, outlier sensitive
R2	Proportion of variance explained by model	0 to 1	Report site ID and n	Higher is better, unstable with limited variance
EWQI	Composite water quality index using entropy weights	Dimensionless (method defined)	Report site ID and n	Lower indicates better quality, disclose

				indicator set and weights
NPI	Nitrate Pollution Index for groundwater	Dimensionless	Report site ID and n	Higher indicates greater nitrate load, method cutoffs vary
HI	Non-carcinogenic Hazard Index from HHRA	Dimensionless	Report site ID and n	HI < 1 typically acceptable, exposure assumptions matter
CR	Cancer risk probability from HHRA	Probability	Report site ID and n	Typical decision band 1e-6 to 1e-4, context specific

This table (1) summarizes evaluation metrics, standardized units or scales, provenance fields, and concise interpretation notes for cross-site comparison.

This section defines a unified metrics table for comparing model performance and water quality risk across sites. Although sampling, sensor precision, and preprocessing differ, units and annotations must be standardized—otherwise summaries mislead. RMSE measures error magnitude and R2 variance explained as diagnostics, but both are scale dependent and sensitive to outliers (Usman et al., 2025). EWQI and NPI summarize water quality, while HI and CR implement HHRA bands (HI < 1; CR 1e-6 to 1e-4) (Wei et al., 2025). Hotspot claims and comparisons require geospatial/statistical evidence, provenance, and sample sizes (Barathkumar et al., 2025). Managers predefine triggers and avoid extrapolation.

Discussion

Although severity-first queues can shorten response times, they may defer preventative work; the scheme counters this by pairing typologies of need with adaptive risk bands. Hydrogeochemical hotspot mapping supports targeted scheduling aligned with SDG aims, but effects are context-bound (Dange et al., 2025). Spatial scale and buffers reshape radii and routing (Lee et al., 2025). Integrating farm and community data can raise responsiveness, yet utility hinges on sampling frequency, coverage, and standardization (Falconer et al., 2025). Connectivity remains the bottleneck. Trained staff and diagnostic kits are prerequisites. Evaluate percent change in route length, days-to-inspection, risk responsiveness, feasibility, and equity safeguards.

Policy Implications

This section converts the prioritization model into actionable governance, financing, and operational levers. Although budgets and staff are tight, risk-based scheduling that weights severity, vulnerability, and service-impact can improve equity and responsiveness over chronological or proximity rules. Integrate hydrogeochemical signals into inspection queues and compliance triggers, grounded in SDG-relevant evidence from Vellore's groundwater analysis (Dange et al., 2025). Address spatial-scale sensitivities for buffer design, route clustering, and cross-jurisdiction coordination; buffer performance is scale dependent (Lee et al., 2025). Instruments include risk-adjusted funding formulas, community-feedback incentives, data-sharing protocols, and adaptive monitoring cycles. Claims of gains, risk responsiveness, and savings require validation.

Limitations

Although distributed sites can provide novel data, such claims need standardization and direct empirical support (Falconer et al., 2025). Sparse coverage, temporal gaps, sensor/reporting errors, and community inputs skew priorities toward accessible or vocal areas; staffing, access, backlogs, and response latency cap coverage, and digital reporting may exclude. Non-identifiability, typology sensitivity, and deterministic scores warrant Bayesian calibration and uncertainty quantification and sensitivity analyses (Kaurila et al., 2025). Transferability is weak where failure modes or reporting differ, ground-truth is scarce, and windows are short, prefer confidence bounds and scenario ranges, and avoid generalizing simulated gains across geographies or governance.

Conclusion

This paper advances a practical prioritization model unifying typologies of need, severity tiers, and real-time community input to convert multi-criteria risk into ranked inspections and trigger-based dispatch. Although settings vary, the scheme yields actionable choices for scarce teams. Expected gains include coverage, faster response, and lower cost; they depend on data quality, assumptions, and validation. Policy entry points: standards, procurement, reporting. Metrics: flexibility, savings, coverage, risk responsiveness, feasibility. Limitations include data sparsity, environmental variability, and model sensitivity. Future pilots and sensitivity analyses should incorporate land-use and climate drivers and supported climate-management simulations (Palmate et al., 2025; Lee et al., 2025).

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