Environmental Science Water Research & Technology

ROYAL SOCIETY OF CHEMISTRY

PAPER

View Article Online
View Journal

Cite this: DOI: 10.1039/d5ew00920k

Bayesian network analysis infers the importance of post-construction support in maintaining the functionality of pit latrines and septic systems across 12 countries

Sarah Lebu * and Ryan Cronk

Pit latrines and septic systems are widely used in low-income countries across sub-Saharan Africa. Despite their critical role in providing basic sanitation, these systems face challenges in maintaining functionality due to issues such as overflowing and leakage, posing significant public health risks. This study examined operations and maintenance (O&M) factors affecting the functionality of on-site sanitation systems, focusing on overflow and leakage patterns, and explored strategies to enhance system performance. Data from 18 534 sanitation facilities across 12 countries, comprising 94% pit latrines and 6% septic systems were analyzed. Using a Bayesian Belief Network analysis, the analysis identified factors influencing system functionality, including desludging frequency, structural damage, and flood risk. Among the systems analyzed, 28% showed evidence of overflowing (29% pit latrines, 17% septic systems), and 24% showed evidence of leakage (24% pit latrines, 14% septic systems). Including flood risk in the model increased overflow rates by 1% and leakage rates by 4% in high-risk flood-prone areas. System performance was primarily influenced by desludging frequency, floor and structural integrity, and the availability of maintenance personnel. Simulations indicated that uniformly implementing frequent desludging across the network had the greatest influence, reducing overflow rates by 72% and leakage rates by 17% relative to current conditions. These findings suggest that post-construction support, such as regular desludging and access to qualified repair personnel, could substantially improve system reliability, particularly in high-risk flood-prone areas, and should be prioritized in sanitation policy and infrastructure design.

Received 19th September 2025,
Accepted 22nd December 2025

DOI: 10.1039/d5ew00920k

rsc.li/es-water

Water impact

Safe sanitation protects water resources and public health, yet common on-site systems frequently leak or overflow, contaminating surface and groundwater. A Bayesian network analysis of 18 534 facilities across 12 countries shows that post construction support, particularly timely desludging and repairs to slabs and superstructures, is critical for sustaining functionality, reducing contamination risks, and ensuring climate-resilient sanitation services.

Introduction

The primary function of sanitation systems is to collect and remove human waste from living areas, reducing the risk of spreading fecal pathogens.[1] Maximum benefits are achieved only when facilities are continuously operated in accordance with acceptable standards.[2] Accordingly, operations and maintenance (O&M) must be carried out effectively. In practice, O&M receives less attention than design and construction, and even well-constructed infrastructure will eventually fail without proper maintenance.[3] The consequences include non-functioning systems that harm the environment and threaten public health. Unsafe sanitation is responsible for approximately 432 000 diarrheal deaths annually, along with substantial burdens of other diseases.[4,5]

The term 'O&M' encompasses distinct functions across the sanitation value chain.[6] Operations refer to daily activities for managing infrastructure, including the collection, treatment, and disposal or reuse of excreta or wastewater.[7] Maintenance involves technical tasks to keep systems functioning optimally, including: (1) preventive maintenance to ensure safe, efficient, and continuous operation at low cost; (2) corrective maintenance, such as minor repairs,

The Water Institute, Department of Environmental Sciences and Engineering, University of North Carolina at Chapel Hill, 4114 McGavran Hall, 135 Dauer Drive, Campus Box #7431, NC 27599, Chapel Hill, North Carolina, USA. E-mail: slebu@unc.edu

unclogging, desludging, or pump fixes; and (3) crisis maintenance, undertaken in response to breakdowns, natural disasters, or user complaints, including major repairs, rehabilitation, system expansion, and new connections.[8] Maintenance requires skills, tools, and spare parts. Inadequate O&M has long been recognized as a barrier to sustainable water and sanitation services. For example, 30–60% of rural water systems fail due to insufficient O&M.[9] While there are few comparable data for sanitation systems, failure rates are likely similar.

Effective O&M is essential for the long-term functionality and sustainability of sanitation systems. Well-maintained systems have a longer infrastructure lifespan, fewer repair needs, and lower recurrent costs.[9] They foster user acceptance and protect public and environmental health. Davis *et al.*[3] found that improved use and maintenance enhanced system functionality, reduced odors, ensured cleanliness, supported effective waste treatment, and decreased open defecation while increasing user perceptions of safety and dignity. Successful O&M models include trained personnel maintaining public toilets in Austria, private-sector management of UDDTs in Kenya, and user training with clear responsibility assignment in Ugandan schools, all of which improved efficiency, resource recovery, acceptance, and sustained usage.[10] Conversely, many sanitation failures are linked to poor management, inadequate planning, and insufficient funding, contributing to persistently high failure rates.[11] In Kenya, O&M of resource-recovering systems involved multiple stakeholders, and 86% were willing to use a facility without bearing responsibility for its maintenance, highlighting the need for solutions beyond households.[2]

O&M of sanitation systems faces persistent challenges. Variability in system types, construction quality, desludging practices, and usage complicates maintenance. Manga *et al.*[12] reported that system performance is closely linked to facility ownership and users' understanding of the technology. Financial and technical constraints in low-income countries frequently impede sustained O&M, resulting in unsafe infrastructure and service failures.[13] Different steps along the sanitation value chain require distinct skills, resources, and responsibilities, often fragmented among multiple stakeholders, with roles often not clearly delineated.[8] Funding mechanisms and responsibilities remain unresolved, with many toilet operators unpaid and critical expenses, such as desludging, rarely budgeted for.[8,14] Consequently, users and service providers often favor low-maintenance technologies that demand minimal routine upkeep.[15] Moreover, costs vary widely across technologies, ranging from 6% to 60% of total lifecycle costs,[14] and social or cultural factors further influence effectiveness.[16] Taken together, the evidence indicates that weak O&M – driven by unclear roles, limited funding, or low technical capacity – undermines sanitation investments and service reliability.

Despite the recognized importance of O&M, research has largely focused on select technologies or contexts, leaving critical knowledge gaps. Prior studies have concentrated on resource-oriented sanitation systems[2] or the allocation of roles, responsibilities, and funding mechanisms.[9,16] Research on school Water, Sanitation, and Hygiene (WASH) programs has addressed role assignment,[6,17,18] technical capacity and expertise,[7] economics of O&M,[19] and the availability of supplies.[18] Many of these studies are qualitative, rely on expert opinion, and involve small sample sizes. Empirical studies quantifying the relative importance of O&M tasks for improving sanitation system functionality remain rare. Without robust evidence on which management approaches are most effective in specific contexts, decisions risk being made on uncertain grounds, potentially leading to the adoption and scaling of inappropriate solutions.

To address evidence gaps, this study applied Bayesian belief network (BBN) models to analyze, predict, and rank O&M strategies using a large cross-sectional dataset. BBNs are well-suited for modeling uncertainties in complex environmental systems and have been increasingly applied in environmental and climate research.[20–28] The study leveraged BBNs to estimate the relative contributions of different management strategies to improved sanitation system functionality, while accounting for variations driven by extreme weather events, seasonality, country-specific conditions, and other contextual factors. Results will provide actionable insights for policymakers and practitioners seeking to develop effective sanitation management strategies and to ensure sustainable service delivery, particularly in the context of climate change.

Bayesian belief networks (BBNs) provide a flexible probabilistic framework for representing dependencies and uncertainty in complex environmental systems. They have been increasingly applied in water and sanitation research to evaluate service continuity,[20] contamination risks,[24,25,29,30] and adaptation options under climate stressors.[31] BBNs are particularly well-suited to this study because they can integrate diverse data sources, capture interactions among operations and maintenance tasks, and quantify the relative contribution of multiple factors to system functionality. The study applied BBNs to identify and rank O&M strategies that improve the performance of pit latrines and septic systems across varied climatic and programmatic contexts.

Materials and methods

Data

This study involved a secondary analysis of survey data collected to evaluate World Vision's WASH programs across 12 sub-Saharan African countries: Ethiopia, Ghana, Kenya, Malawi, Mali, Mozambique, Niger, Rwanda, Tanzania, Uganda, Zambia, and Zimbabwe. World Vision selected these countries because they featured ongoing large-scale WASH programming, operational feasibility for standardized data collection, and sufficient geographic and contextual diversity to support cross-country analysis. The authors did not select the countries; rather, the study involved secondary analysis of this harmonized dataset. The sampling strategy has been described in detail elsewhere.[32] Briefly, primary sampling units (PSUs) were defined using administrative clusters and divided into areas with active WASH programs and comparison areas. Fifty-six clusters were randomly selected per group using probability proportional to size. Large PSUs were split into secondary sampling units (SSUs), and one SSU was randomly selected. Within each cluster or SSU, 25 households were randomly sampled. In Tanzania and Zimbabwe, districts with active programs were first identified, and comparison administrative units without programs were randomly selected; clusters were then sampled using the same PPS approach. Household surveys, administered to female heads of households, covered water sources, sanitation practices, and demographics, and combined structured interviews with direct observation. Survey data were collected by experienced in-country supervisors and enumerators. Surveys were translated, locally verified, and collected *via* the mobile platform mWater to ensure real-time data entry, quality control, and data integrity.

Flood data were obtained from the World Resources Institute (WRI) Aqueduct Global Water Risk Mapping Tool, an established global dataset that estimates riverine flood hazard at approximately 1 km^2 resolution using hydrologic and hydraulic modeling combined with climate and socio-economic projections.[33] The dataset provides modeled flood return periods ranging from 2 to 1000 years, generated using the CaMa-Flood global hydrodynamic model, combined with CMIP6 climate projections and socioeconomic scenarios, to estimate global riverine flood hazard. In the current study, each sanitation facility was first spatially joined to the underlying flood-hazard raster in ArcGIS using point-to-raster analysis, thereby enabling the extraction of the corresponding flood-return-period value for each facility. Next, to convert these continuous return-period values into analytical categories, we then applied a quantile classification in ArcGIS to generate four risk levels—low, medium, high, and very high. Quantile classification is widely used in hazard mapping because it produces balanced categories and enhances comparability across heterogeneous geographic settings.

Study outcomes and variables

Following established modeling practices,[34] variables influencing sanitation system functionality were identified through a three-step process that combined a literature review, expert consultation, and empirical evidence. We focused on two primary indicators of sanitation system functionality – overflow and leakage – each treated as a binary outcome. Overflow occurs when inflow exceeds the containment capacity, resulting in backups or surface spills, whereas leakage denotes structural failure that allows excreta to escape into the environment.[3]

Guided by prior research and expert judgement, the study hypothesized that functionality is shaped by three O&M domains: emptying practices, cleaning and hygiene management, and structural repair and maintenance. Twelve variables were selected to represent these domains (Table 1). Indicators related to emptying practices included observed

Table 1 Definitions and states of variables included in the Bayesian network analysis of sanitation system functionality

Nodes (short name)[a]	Description of variable	Output states
Overflowing	Evidence of facility being full and discharging waste onto the ground	No/yes
Leaking	Evidence of waste escaping *via* structural defects, regardless of fullness	No/yes
Flood risk	Likelihood of flooding based on historical flooding frequency in the area	Low/medium/high
Facility fee	Whether users pay a fee to use the facility	No/yes
Cleaning person	Refers either to a hired caretaker responsible for cleaning shared facilities or, in the case of single-household latrines, to a household member identified as responsible for routine cleaning and maintenance	No/yes
Repair person	Availability of a skilled person to repair the facility. This typically includes masons, carpenters, or local artisans who can repair slabs, walls, pedestals, or superstructures	No/yes
Desludging needed	Facility requires desludging due to accumulated waste	No/yes
Emptied once	Facility has been emptied at least once in the past	No/yes
Structural damage	Repairs needed on superstructure (cracks, pedestal/slab damage)	No/yes
Floor condition	Condition of the floor or slab	Severely damaged/moderately damaged/good
Visible excreta	Presence of urine or feces on the floor	No/yes
Cleanse material	Users employ appropriate cleansing materials (toilet paper or water)	Not available/available
Sharing facility	Facility shared with other households or public	No/yes
Water supply	Continuous water availability at the facility	Continuous/non-continuous

[a] Short names as used in the Bayesian network analysis program.

need for desludging and reported history of emptying. Cleaning practices were assessed by the presence of a designated cleaner, visible fecal contamination on floors or walls, the availability of water for cleaning, and the use of appropriate cleaning materials (*e.g.*, water, toilet paper). Structural integrity was assessed by the condition of the superstructure (*e.g.*, cracks or pedestal damage), floor condition, availability of skilled repair personnel, and whether users paid a fee for access. Flood hazard was included as a separate contextual variable, expressed as a standardized index derived from modeled flood frequency.

A detailed justification for each variable is provided (Table S1). To corroborate the selected variables using empirical data, we first conducted bivariate and adjusted logistic regression analyses to assess associations between the candidate variables and the two functional outcomes. Variables with statistically significant associations ($p < 0.05$) were retained for inclusion in the BBN model, ensuring the model is grounded in both conceptual knowledge of relevant domains and empirical evidence.

Bayesian belief networks

Bayesian belief networks (BBNs) are probabilistic graphical models that represent uncertainty in complex systems. Originating from artificial intelligence, they combine probability theory and graph theory to model dependencies between variables based on Bayes' theorem of conditional probability. A BBN consists of a directed acyclic graph (DAG) where nodes represent variables, and directed edges indicate probabilistic dependencies. Conditional probability distributions define the strength of these relationships, allowing BBNs to manage uncertainty effectively.[35] Conditional probability functions parametrically determine Bayesian networks. Generally, those parameters are specified in a conditional probability table (CPT). The CPT contains a set of probability values for all possible combinations of parent and child node states. The probabilities or parameters are the materials on which the Bayesian theorem operates and provide evidence to inform the model. In a typical BBN structure, parent or originating nodes are linked to child or receiving nodes through arrows, signifying that the parent node's factor directly affects the child node's outcome. This directional description of a probabilistic network enables consideration of the relationships between factors and consequences, thereby identifying important variables and pathways to outcomes.

Model construction, parametrization, and evaluation

Good model practices were followed.[34] The model was designed using evidence and expert judgment to compile a comprehensive list of O&M tasks essential for maintaining sanitation infrastructure. Several notable publications contributed to developing the BBN model, including a training package for implementing effective operation and maintenance of rural water supply and sanitation services in low- and middle-income countries,[9,16] and the World Health Organization Guidelines on Sanitation and Health.[36] The referenced WHO Guidelines for Sanitation and Health (Geneva) are global guidelines applicable across all countries, including those in sub-Saharan Africa. They are not country-specific but serve as the international standard for sanitation safety planning. The cleaned datasets for each country were exported from Stata and imported into the Netica software.[37] The study used two separate case files randomly divided from the original dataset. The first case file was a training set (n = 17 221; 80%) for learning the model. The second case file constituted the testing data (n = 4306; 20%).

Based on the literature, a conceptual model outlining potential factors influencing the functionality of sanitation systems was developed, with evidence of overflow and leakage as the primary outcomes. The conceptual model comprised 12 nodes classified into clusters of cleanliness tasks, repair and maintenance tasks, and emptying practices. The Netica software estimates the CPT values using the expectation maximization (EM) algorithm. The training dataset was entered into the model as findings, and the EM algorithm was applied to generate the CPT values used by Netica. The unit of analysis was the sanitation facility. Although 18 536 households were surveyed, households served to identify and describe the facilities they used. Thus, while households provided the data, all statistical analyses were conducted at the level of the sanitation facility. The CPTs for each node were derived empirically from the observed dataset. For each combination of parent-node states, conditional probabilities were estimated as the relative frequencies of the child-node states (*i.e.*, maximum-likelihood estimates). This empirical approach was chosen due to the large sample size and to avoid introducing subjectivity from expert expectations, which may vary by context.

The effect of each predictor variable was evaluated by comparing the prior probability of a sanitation system being functional (determined from raw data) with the posterior probability, which represents the conditional probability of the target given each predictor node's values. This assessment does not imply causation but instead quantifies the strength of the association while accounting for other variables in the network. The reduction in uncertainty between the prior and posterior states of the target for each predictor, known as mutual information, shows the most influential predictive variables.[38]

The model's performance was assessed using ten-fold cross-validation, measuring the area under the receiver operating characteristic (ROC) curve. This curve illustrates the relationship between the actual and false positive rates across varying probability thresholds for classifying the binary outcome—in this case, whether a toilet is functional or nonfunctional. A ROC score of 1 signifies a model with perfect discrimination between outcomes, whereas a score of 0.50 indicates that the model's predictive ability is no better than random chance.[39] Predictive inference was conducted to find influential nodes that help us prioritize O&M actions to improve sanitation system functionality. This was done by setting the state of a specific node to 100% and observing the resulting change in the posterior probability of the outcome node. For example, to examine the influence of pit latrine emptying history on functionality, the state emptied once (indicating that a facility had been emptied at least once since it's construction) was set to 100%, and the corresponding updated probability of detecting overflows or leakages was assessed. This was done for all states in all nodes. Other model assessments conducted were logarithmic loss, quadratic loss, and spherical payoff.

Ethics statement

The UNC-Chapel Hill Institutional Review Board (IRB #23-1944) approved the use of the data for analysis. All procedures were conducted in accordance with ethical standards to protect participants' rights and confidentiality throughout the study.

Results

Descriptive results for functionality and associated factors

Data from 18 534 on-site sanitation facilities were analyzed, consisting of 94% pit latrines and 6% septic systems (Table 2). Overall, 28% of facilities exhibited overflowing, and 24% exhibited leaking. Both conditions were more common in pit latrines than in septic systems (overflows: 29% *vs.* 17%; leakages: 24% *vs.* 14%). Fewer than 1% of facilities required users to pay an access fee, and 73% had skilled maintenance and repair personnel available.

Structural conditions varied: 28% of facilities exhibited visible structural damage, while floor condition ranged from moderately damaged (46%) to severely damaged (42%), with only 12% in good condition. Approximately 6% of the facilities had been emptied at least once, although 7% were full and required immediate desludging.

Cleanliness and maintenance indicators also varied widely. A designated cleaning person was present in 74% of facilities, and excreta was visible on slabs or walls in 46% of facilities. Flies were observed in 61% of facilities. Appropriate cleansing materials were available in 17% of facilities, and only 20% had a continuous water supply; the remaining 80% relied on intermittent sources.

Approximately 21% of facilities were shared with other households or the public. With respect to service quality, 65% of facilities met the criteria for improved sanitation, whereas 35% were classified as unimproved.

Table 2 Descriptive statistics of 18 534 surveyed pit latrines and septic systems

Variable	*n*	%
Sanitation technology type		
Pit latrine	17 404	93.9
Septic system	1130	6.1
Evidence of overflowing		
Yes	5161	27.9
No	13 373	72.2
Evidence of leaking		
Yes	4369	23.6
No	14 165	76.4
Facility fee		
Paid	147	0.8
Not paid	18 387	99.2
Availability of skilled repair personnel		
Yes	13 466	72.7
No	5068	27.3
Evidence of structural damage		
Yes	5215	28.1
No	13 319	71.9
Condition of the floor		
Severely damaged	7775	42.0
Moderately damaged	8570	46.2
Good condition	2189	11.8
Emptied at least once in the past		
Yes	1057	5.7
No	17 477	94.3
Desludging needed		
Yes	1355	7.3
No	17 179	92.7
Availability of a designated person to clean the facility		
Yes	13 797	74.4
No	4737	25.6
Excreta visible on the slab and walls		
Yes	8565	46.2
No	9969	53.8
Presence of flies in the facility		
Yes	11 229	60.6
No	7305	39.4
Availability of appropriate cleansing materials		
Yes	3196	17.2
No	15 338	82.8
Continuous supply of water		
Yes	3769	20.3
No	14 765	80.0
Sharing facilities with other households or the public		
Yes	3797	20.5
No	14 737	79.5
Flood risk		
Low risk	3871	20.9
Medium risk	4057	21.9
High risk	10 606	57.2

Bayesian network analysis

Two BBN models were developed for the primary outcomes: evidence of overflows and evidence of leakages (Fig. 1 and 2). Each model shows state beliefs for all nodes, with belief bars indicating the most likely outcome states. The black bars represent the initial probability distributions (prior, conditional, and posterior) derived from the training dataset and reflect the factors influencing sanitation system functionality.

In the Bayesian network with evidence of overflowing as the outcome, the most influential predictors were desludging need, emptying frequency, structural damage, and prior emptying history. Continuous water supply, user fees, and cleansing material use showed minimal influence. Sub-analyses restricted to pit latrines and septic systems identified similar influential variables for pit latrines. In contrast, flood risk emerged as a stronger predictor for septic

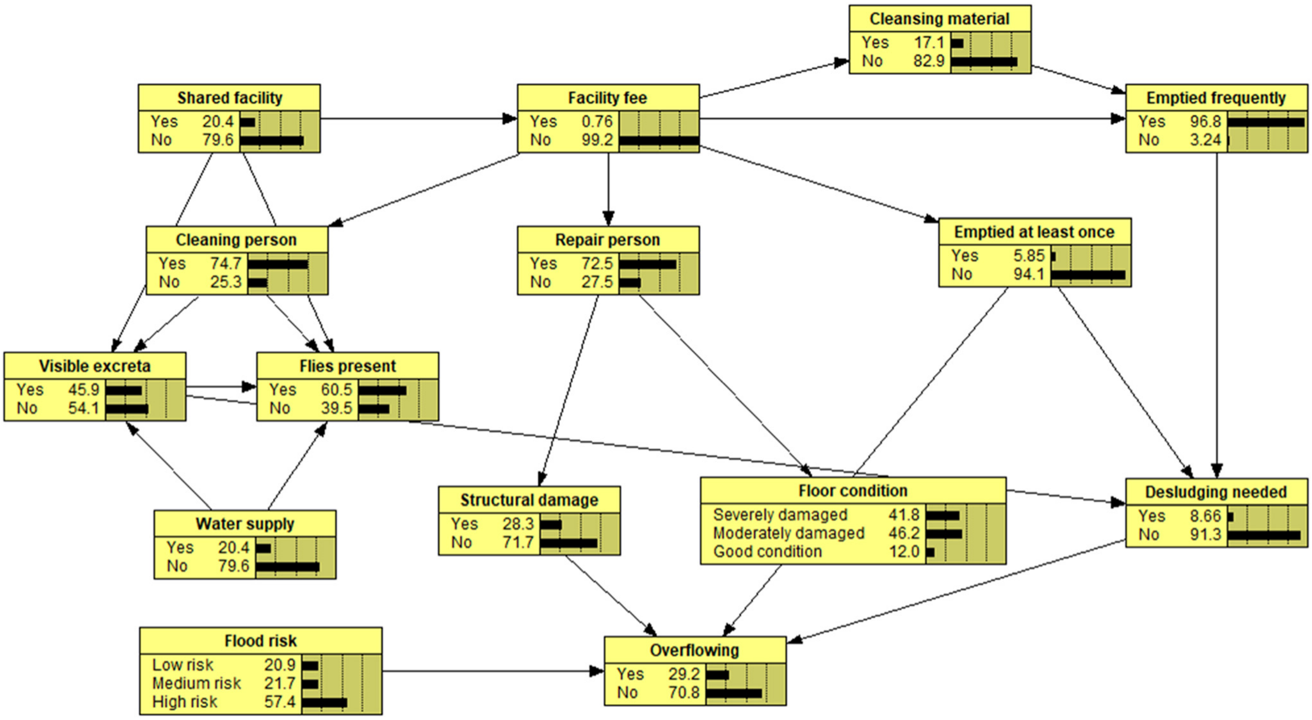

Fig. 1 Bayesian belief network of factors influencing overflow rates in on-site sanitation systems. The network represents factors influencing overflow rates across 18 534 pit latrines and septic systems in 12 sub-Saharan African countries. Arrows indicate the direction of influence between variables based on conditional dependencies identified in the Bayesian analysis.

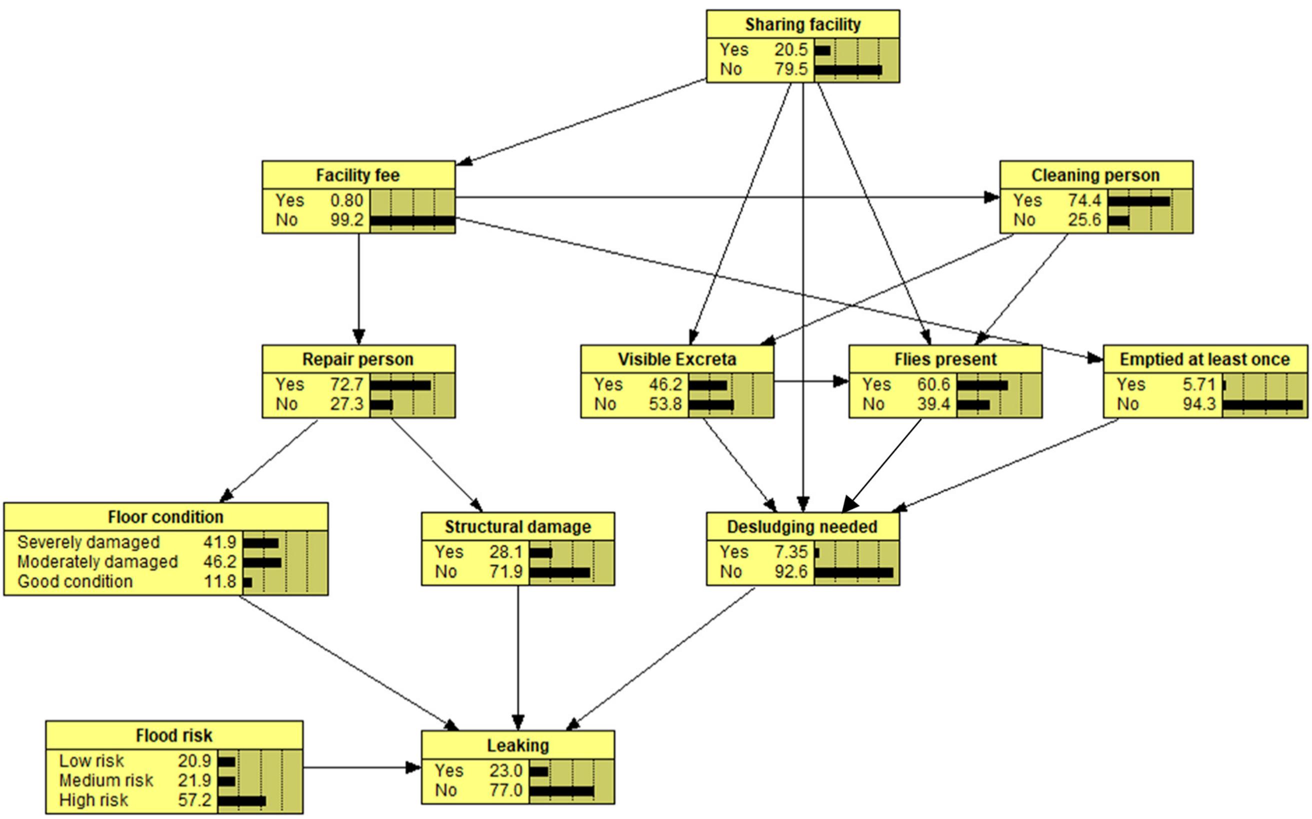

Fig. 2 Bayesian belief network of factors influencing leakage rates in on-site sanitation systems. The network represents factors influencing overflow rates across 18 534 pit latrines and septic systems in 12 sub-Saharan African countries. Arrows indicate the direction of influence between variables based on conditional dependencies identified in the Bayesian analysis.

Table 3 Factors influencing evidence of overflowing in 18 534 sanitation systems across 12 sub-Saharan African countries, as identified through Bayesian network analysis. The most influential variables include desludging need, emptying frequency, structural damage, and prior emptying. In contrast, access to a continuous water supply, user fees, and the use of cleansing materials had the least influence on the occurrence of overflows

Node	Mutual info	Percent	Variance of beliefs
Overflowing	0.86755	100	0.2055185
Desludging needed	0.15768	18.2	0.0456229
Emptied frequently	0.00920	1.06	0.0029444
Structural damage	0.00267	0.308	0.0007743
Emptied at least once	0.00065	0.0745	0.0001773
Flood risk	0.00060	0.0695	0.0001705
Visible excreta	0.00032	0.0364	0.0000902
Repair person	0.00003	0.00374	0.0000093
Flies present	0.00001	0.0016	0.0000040
Shared facility	Negl[a]	0.000376	0.0000009
Cleaning person	Negl	0.000252	0.0000006
Floor condition	Negl	Negl	0.0000002
Cleansing material	Negl	Negl	0.0000002
Facility fee	Negl	Negl	0.0000001
Water supply	Negl	Negl	Negl

[a] Negl means the value is small and negligible.

systems, with its influence increasing by an order of magnitude compared with the full model. The reduction in uncertainty between prior and posterior probabilities for each predictor further illustrates which variables were most and least influential in predicting overflows (Table 3).

In the second model, with evidence of leakages as the outcome, the factors that most strongly influenced the probability of leakages were desludging need, floor condition, flood risk, structural damage, and the availability of a repair person. In contrast, facility fees, the presence of a cleaning person, and the presence of flies had minimal influence on leakage rates (Table 4). The relative importance of these predictors was consistent for both pit latrines and septic systems.

3.3 Model performance

Model predictive accuracy was evaluated using both the full dataset and a 20% hold-out testing dataset (n = 3707 observations). The overflows model achieved an area under the ROC curve (AUC) of 66.2% in the full dataset, indicating fair predictive performance.[39] By contrast, the leakages model reached an AUC of 58.6%, reflecting weaker predictive capability (Fig. 3). Stratifying the dataset by sanitation technology improved model performance, with the AUC increasing by 0.7 percentage points for pit latrines and six percentage points for septic systems. These metrics indicate that the models distinguish between functioning and non-functioning systems better than chance (in approximately 87% of cases), though performance is stronger for overflows than for leakages.[40] Confusion matrices and additional performance diagnostics are provided in the SI (S1 File).

3.4 Factors influencing system functionality

Simulation analyses were conducted under best- and worst-case conditions by specifying the state of each controllable

Table 4 Factors influencing evidence of leaking in 18 534 sanitation systems across 12 sub-Saharan African countries, as identified through Bayesian network analysis. The most influential variables include the desludging need, floor condition, flood risk, structural damage, and availability of a repair person. In contrast, facility fees, the presence of a cleaning person, and the presence of flies did not influence evidence of leakages

Node	Mutual info	Percent	Variance of beliefs
Leaking	0.77860	100	0.1772837
Desludging needed	0.00791	1.02	0.0021842
Floor condition	0.00556	0.714	0.0014057
Flood risk	0.00090	0.115	0.0002192
Structural damage	0.00047	0.0604	0.0001167
Repair person	0.00021	0.0276	0.0000532
Emptied at least once	0.00004	0.00474	0.0000092
Visible excreta	0.00002	0.00238	0.0000046
Shared facility	0.00000	0.000216	0.0000004
Flies present	Negl[a]	0.000126	0.0000002
Facility fee	Negl	Negl	Negl
Cleaning person	Negl	Negl	Negl

[a] Negl means the value is small and negligible.

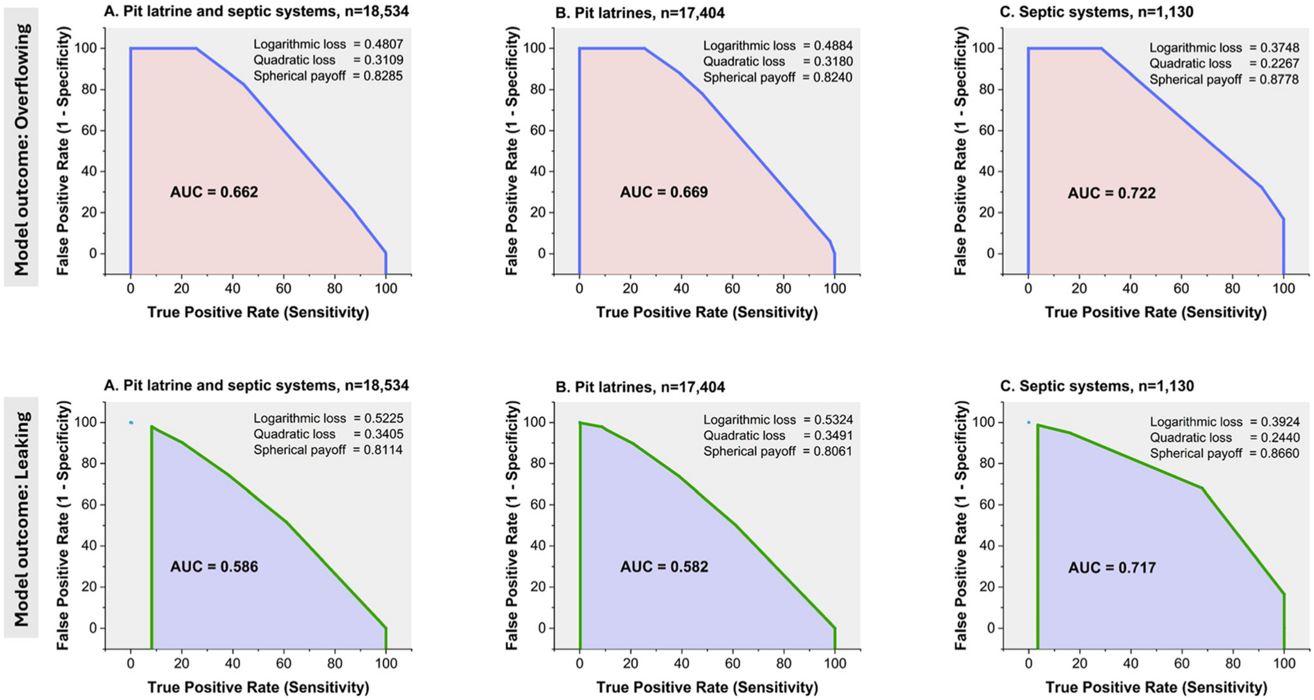

Fig. 3 Receiver-operating characteristic curves showing the performance of the BBN models run in the study. The area under the ROC curve (AUC) ranges from 0.722 to 0.582, indicating the model has moderate discriminatory ability. While the model outperforms random guessing (AUC = 0.5), there remains room for improvement in its predictive accuracy.

variable. The best-case scenario assumed: facility requires desludging (no), structural damage (none), floor condition (good), repair person available (yes), designated cleaner available (yes), flies present (yes), visible excreta on slabs (no), facility emptied at least once (yes), facility emptied frequently (yes), continuous water supply (yes), and facility fee collected (yes).

Conversely, the worst-case scenario assumed: facility requires desludging (yes), structural damage (present), floor condition (poor), repair person available (no), designated cleaner available (no), flies present (no), visible excreta on slabs (yes), facility emptied at least once (no), facility emptied frequently (no), continuous water supply (no), and facility fee collected (no).

In the best-case scenario, the predicted likelihood of leakage decreased from 23% to 18%, whereas under the worst-case scenario, it increased to 55%. For overflows, probabilities declined slightly from 28% to 27% under best-case assumptions but rose sharply to 93% under worst-case conditions.

Universal simulations of individual variable states showed that ensuring all containment systems underwent desludging reduced overflowing by 72 percentage points, while frequent emptying and prior emptying history reduced overflowing by 34 and 26 percentage points, respectively (Table 5). For leakage, the strongest predictors of increased risk were the need for desludging and severely damaged floors, which increased leakage probabilities by 17 and 9 percentage points.

Simulated optimal emptying practices, including timely desludging, frequent emptying, and a history of prior emptying, resulted in a 7% reduction in overflows and a 2% decrease in leakages. In contrast, simulating ideal cleanliness conditions (the presence of a cleaning person, a continuous water supply, the absence of visible excreta and flies, and the availability of cleansing materials) produced minimal improvements: approximately a 1% reduction in overflows and less than a 1% reduction in leakages.

Actions within the control of users, such as facility fee collection, the presence of a cleaning staff, and adherence to cleansing materials, had little effect on overflow or leakage rates. Although facility fees did not directly predict system failure, they were associated with better flood conditions, improved structural integrity, and greater availability of skilled repair personnel.

Facilities located in high-risk flood zones showed a 1% increase in overflow rates and a more than a 1% increase in leakage rates, whereas those in low-risk zones exhibited reductions of 2% and 4%, respectively.

4. Discussion

The Bayesian network models consistently identified desludging needs, structural integrity, and flood risk as the primary determinants of sanitation system functionality, while factors such as user fees and the presence of cleaning staff contributed minimally. Although predictive accuracy varied across outcomes, the models provided a structured

Table 5 Predicted change in rate of functionality when a positive state finding in the predictive node is made 100%

Scenarios	State outputs	Model 1: overflowing		Model 2: leaking	
		Predicted Rate (%)	% point change	Predicted Rate (%)	% point change
Desludging needed	Yes	99.3	−72.2	39.6	−16.6
	No	22.9	4.2	21.7	1.3
Evidence of structural damage	Yes	32.3	−5.2	24.8	−1.8
	No	25.4	1.7	22.4	0.6
Emptying done frequently	Yes	26.9	0.2	n/a	
	No	61.1	−34.0		
Emptied at least once in the past	Yes	27.0	0.1	24.3	−1.3
	No	53.1	−26.0	23.0	0.0
Visible excreta on slabs and walls	Yes	28.0	−0.9	23.3	−0.3
	No	25.5	1.6	22.8	0.2
Flood risk	Low risk	24.8	2.3	21.2	1.8
	Medium risk	25.9	1.2	21.5	1.5
	High risk	27.8	−0.7	24.3	−1.3
Facility fee	Yes	31.1	−4.0	23.0	0.0
	No	27.0	0.1	23.0	0.0
Flies present	Yes	27.3	−0.2	23.1	−0.1
	No	26.7	0.4	23.0	0.0
Condition of floor	Severely damaged	35.4	−8.3	31.5	−8.5
	Moderately damaged	29.7	−1.3	24.1	−1.1
	Good condition	25.0	3.4	19.5	3.5
Cleaning person available	Yes	28.3	0.1	23.0	0.0
	No	18.5	−0.1	23.1	−0.1
Sharing facility	Yes	28.6	−0.2	23.2	−0.2
	No	28.3	0.1	23.0	0.0
Continuous water supply	Yes	28.4	0.0	n/a	
	No	28.4	0.0		
Repair person available	Yes	28.0	0.4	22.6	0.4
	No	29.4	−1.0	24.2	−1.2
Appropriate cleansing materials	Yes	28.5	−0.1	n/a	
	No	28.4	0.0		

The response category under investigation was set to 100% in each scenario. The predicted output rate is the predicted prevalence in each scenario. The percentage-point change is the difference between the predicted prevalence in each scenario and the existing prevalence in the actual data (overflowing 27.1%, not overflowing 72.9%, and leaking 23%, not leaking 77%). The percentage-point changes highlighted in green indicate positive predictors of functionality, whereas those highlighted in red indicate negative predictors. Darker shades of color correspond to large predictive changes. The color gray represents no change.

basis for evaluating sanitation system functionality and identifying priority interventions across diverse contexts.

The analysis revealed substantial variation in sanitation system performance, as reflected in the rates of facility overflow and leakage. These differences appear to be shaped by a combination of system characteristics, maintenance practices, and environmental conditions. Similar patterns have been documented elsewhere: Peal *et al.*,[41] in a study of 31 cities, reported that 14% of pit and tank contents that were not emptied overflowed, leaked, or directly discharged waste into the environment. Additional research reinforces the influence of geophysical conditions on system performance. For example, areas with high groundwater tables or permeable sandy soils often exhibit compromised structural integrity, leading to increased leakage.[42] Conversely, compact soils such as clay and flat terrain have been shown to enhance the longevity and maintainability of sanitation structures, as locally available clay bricks reduce costs and support more durable construction, as observed in rural Kenya, Zambia, Nepal, and Bhutan.[43]

Resource availability and fee structures also influenced system functionality. Revenue from user fees can support routine maintenance, repairs, infrastructure expansion, staff training, and hygiene promotion, thereby improving service delivery and sustainability.[44,45] However, in low-income settings, fees can pose barriers to access, particularly in informal settlements.[46] Kumar *et al.*,[47] conducted a study in similar settings in India, highlighting that fees must be carefully managed to avoid exacerbating inequalities and hindering access for vulnerable populations.

Desludging emerged as a critical determinant of sanitation system performance. Facilities that were emptied regularly had markedly lower rates of overflow and leakage, underscoring the importance of scheduled maintenance. This finding is consistent with earlier studies demonstrating that adequate desludging is central to ensuring system functionality.[3,12] Pit latrines were particularly vulnerable to overflow, whereas septic systems – especially those in flood-prone regions – were more susceptible to leakage, likely due to differences in design and site-specific environmental conditions.[48] Evidence from Tamil Nadu, India supports this pattern: Davis *et al.*[49] reported that households typically desludged only during emergencies, with little advance planning, resulting in frequent sewer overflows during the rainy season. A monthly sanitation fee was proposed to fund and encourage more regular emptying. Similar observations were made by Lebu *et al.*[50] who found that more frequent emptying in urban slums reduced the likelihood of overflow in both pit latrines and septic tanks. The World Health Organization (WHO) has likewise emphasized that routine maintenance and emptying are essential for functional sanitation systems in low-income settings.[9]

In contrast, inadequate emptying accelerates infrastructure deterioration and elevates the risk of overflow and leakage.[51] In Tanzania, Jenkins *et al.*[52] documented that overfilled pit latrines often discharged fecal sludge to overflow into neighborhoods and waterways during the rainy season, creating unsanitary conditions, increasing children's exposure to vectors, and contributing to groundwater contamination. The finding that more than 80% of floors showed moderate to severe damage, yet 92.7% of respondents reported that desludging was not required, highlights structural deterioration as a major concern independent of sludge accumulation. Many pits rely on infiltration rather than periodic emptying, which can mask the need for desludging while allowing structural decay to progress. Addressing this critical red flag requires improved construction standards, routine structural inspections, user education, and targeted subsidies or support for facility rehabilitation.

Study findings highlight the important role of cleanliness and hygiene in maintaining sanitation system functionality. Facilities free of visible excreta exhibited lower rates of overflow and leakage, consistent with earlier work linking cleanliness to improved performance.[12,50] Simiyu *et al.*,[53] for example, found that systems actively cleaned and maintained by users experienced fewer breakdowns, with the presence of designated cleaning personnel significantly reducing failure incidents. In this study, 74% of facilities had a designated cleaner, suggesting that hygiene practices remain an under recognized yet critical component of system functionality. Empirical research on how cleaning practices influence sanitation performance remains limited.

This relationship may manifest differently in single-household latrines than in shared facilities. Most facilities in the dataset were not shared, meaning cleaning responsibilities typically fell to household members rather than designated staff. In single-household settings, cleanliness may serve as a proxy for broader household maintenance behavior: households that consistently keep latrines clean may also be more likely to maintain structural components, monitor pit filling, and arrange timely desludging. Conversely, dirty facilities may reflect broader neglect, increasing the risk of undetected damage, clogging, or delayed emptying—all of which contribute to overflow and leakage. Thus, even without shared use or formal cleaning arrangements, cleanliness remains an indirect but meaningful indicator of overall maintenance practices in single-household systems.

Flood risk also had a notable impact on functionality. Facilities in high-risk flood areas showed a 1% increase in both overflow and leakage, while those in low-risk areas exhibited a 2% decrease in overflow and a 4% reduction in leakage. These findings align with existing evidence identifying flood-prone environments as particularly vulnerable to sanitation system failure.[48,54] Floodwaters can damage containment infrastructure, compromise systems not designed to withstand inundation, and disrupt desludging services, increasing the likelihood of overflow and leakage.[55,56] This reinforces the need for flood-resilient sanitation design and risk-informed infrastructure planning.

Although groundwater and soil contamination were beyond the scope of the dataset analyzed in this study, these pathways are central to understanding the wider environmental and public health consequences of sanitation system failure. Multiple studies in sub-Saharan Africa have documented elevated nitrate and fecal indicator bacteria in groundwater near pit latrine and septic system installations, particularly in high water table areas.[57–61] Structural deterioration of on-site sanitation systems has also been linked to localized soil contamination with enteric pathogens, contributing to exposure through contaminated play areas, household compounds, and floodwater.[62] These findings underscore that overflow and leakage are not isolated facility-level issues but are key drivers of broader environmental contamination.

These findings carry important implications for sanitation policy and practice, especially in low-income and flood-prone areas. Strengthening emptying practices through timely desludging, routine maintenance, and defined desludging protocols could substantially reduce system failures. Model simulations and descriptive data indicate that approximately 28% of facilities exhibited structural damage, while 88% had floors that were moderately or severely damaged, suggesting that a substantial share of failures could be mitigated through basic structural repairs. Additionally, 7% of facilities were full and required immediate desludging, and 40% had never been emptied, highlighting the potential for improved emptying practices to significantly reduce the risk of overflow. Overall, routine maintenance, targeted repairs, and regular desludging could enhance functionality for an estimated 30–50% of facilities in this dataset. Complementing these measures with hygiene promotion and dedicated cleaning personnel may further reduce leakage and contamination risks. Finally, integrating flood risk assessments into sanitation planning and adopting flood-resilient technologies will be increasingly important as extreme weather events intensify under climate change.

4.1 Limitations

This study has several limitations that should be considered when interpreting the findings. First, the cross-sectional nature of the data provides only a snapshot of sanitation system performance at the time of data collection, preventing any causal inference. Second, the dataset did not include alternative on-site technologies (*e.g.*, composting or vault systems), limiting the ability to assess technology-specific variation beyond pit latrines and septic tanks. Third, sanitation functionality was assessed using proxy indicators—overflowing and leaking—that capture visible signs of system failure but may not reflect the full spectrum of performance issues, such as groundwater contamination or subsurface leaching of excreta. Fourth, several potentially important covariates were not available in the dataset, including groundwater table depth, site-specific soil characteristics, and the age of containment systems. These factors likely influence how sanitation systems respond to climate-related hazards and may have strengthened the analysis had they been included. Finally, the flood hazard data were provided at a spatial resolution of approximately 1 km^2, which may not capture fine-scale topographic variation relevant to localized flooding. Flood risk classifications represent long-term modeled hazard levels and do not account for single extreme flood events, which may cause short-term impacts not captured in the dataset.

5. Conclusion

This Bayesian network analysis highlights key determinants of sanitation system functionality in low-resource and flood-prone settings. Desludging frequency, structural integrity, and flood risk emerged as the strongest predictors of overflow and leakage, whereas user fees and the presence of dedicated cleaning personnel contributed minimally to system performance. Pit latrines were more susceptible to overflow, and septic systems – particularly those in flood-prone areas – were more vulnerable to leakage, underscoring the need for technology- and context-specific strategies. Simulations results demonstrate that timely emptying, routine maintenance, and sound hygiene practices substantially reduce failure risks, whereas interventions focused solely on user-controlled factors such as fees or cleaning are offer limited benefits. These insights provide evidence-based direction for prioritizing interventions, designing climate-resilient sanitation systems, and improving resource allocation to enhance the safety, reliability, and sustainability of onsite sanitation services in vulnerable environments.

Conflicts of interest

There are no conflicts to declare.

Data availability

Data for this article are available at The University of North Carolina (UNC) Dataverse at [https://dataverse.unc.edu/dataset.xhtml?persistentId=doi:10.15139/S3/XALHIY].

Supplementary information (SI): this file contains SI that support the analysis presented in the manuscript titled "Bayesian belief network analysis infers the importance of post-construction support in maintaining the functionality of pit latrines and septic systems across 12 countries". The tables and figures provide detailed outputs from the Bayesian belief network models and logistic regression analyses used to assess factors influencing the functionality of on-site sanitation systems, specifically focusing on overflow and leakage outcomes. Table S1: variable selection and justification. Tables S2 and S3: key factors associated with overflow in pit latrines and septic systems based on Bayesian network analysis across 12 sub-Saharan African countries. Tables S4–S30: results from Scoring Rule assessments and logistic regression analyses for models 1–4 (a–c), disaggregated by sanitation type and outcome (overflow and/or leakage). Fig. S1–S12: graphical output from Bayesian network models showing predicted rates of overflows and/or leakages for each model variant, stratified by sanitation type. Fig. S13: diagram illustrating the sample design used in the household survey informing the analysis. See DOI: https://doi.org/10.1039/d5ew00920k.

Acknowledgements

The author gratefully acknowledges the Water Institute at the University of North Carolina at Chapel Hill for providing access to the data used in this study. Sincere thanks are extended to the dedicated team responsible for data collection across all 12 countries. The author also wishes to thank the staff of the Water Institute and World Vision for their supervision, leadership, and invaluable support throughout the project. Special thanks to Darcy Anderson and Catherine McManus for their assistance with the IRB application process.

References

1 E. Tilley, L. Ulrich, C. Luthi, P. Reymond and C. Zurbrügg, *Compendium of Sanitation Systems and Technologies*, 2014.

2 E. Muchiri and E. Muellegger, in *Operation and maintenance strategies for resource-oriented sanitation systems in Nakuru, Kenya*, 2009, Available from: https://www.semanticscholar.org/paper/Operation-and-maintenance-strategies-for-sanitation-Muchiri-Muellegger/c8f4b1c04d968f2ab7aa3b1c3322eea6bb2ccaad.

3 A. Davis, A. Javernick-Will and S. M. Cook, Priority Addressment Protocol: Understanding the Ability and Potential of Sanitation Systems to Address Priorities, *Environ. Sci. Technol.*, 2019, **53**(1), 401–411.

4 L. Andrés, G. Joseph, S. Rana, L. Andrés, G. Joseph and S. Rana, The Economic and Health Impacts of Inadequate Sanitation, 2021, Available from: https://oxfordre.com/environmentalscience/view/10.1093/acrefore/9780199389414.001.0001/acrefore-9780199389414-e-561.

5 J. Wolf, R. B. Johnston, A. Ambelu, B. F. Arnold, R. Bain and M. Brauer, *et al.*, Burden of disease attributable to unsafe drinking water, sanitation, and hygiene in domestic settings: a global analysis for selected adverse health outcomes, *Lancet*, 2023, **401**(10393), 2060–2071.

6 M. Sohail, S. Cavill and A. P. Cotton, Sustainable Operation and Maintenance of Urban Infrastructure: Myth or Reality?, *J. Urban Plan. Dev.*, 2005, **131**(1), 39–49.

7 M. Sohail, S. Cavill and A. Cotton, in *Operation, Maintenance and Sustainability of Services for the Urban Poor: Findings, lessons learned and case studies summary and analysis*, 2001, Available from: https://www.semanticscholar.org/paper/Operation%2C-Maintenance-and-Sustainability-of-for-Sohail-Cavill/bdfc0138b56a1f1f5daef79a507baca1ae041c28.

8 J. Willetts, F. Mills and M. Al'Afghani, Sustaining Community-Scale Sanitation Services: Co-management by Local Government and Low-Income Communities in Indonesia, *Front. Environ. Sci.*, 2020, **8**, DOI: 10.3389/fenvs.2020.00098.

9 F. Brikké and M. Bredero, *Linking technology choice with operation and maintenance in the context of community water supply and sanitation: a reference document for planners and project staff*, World Health Organization and IRC Water and Sanitation Centre, Geneva, Switzerland, 2003.

10 Vienna ATEcoSan Clu, *Operation and maintenance: successful models for O&M of sanitation systems*, EcoSan Club, Vienna, Austria, 2009, vol. 2, p. 31.

11 A. Bräustetter, Operation and Maintenance of Resource-Oriented Sanitation Systems in Peri-Urban Areas, *Diploma Thesis*, Fachhochschule Weihenstephan, Triesdorf, Germany, 2007.

12 M. Manga, P. Kolsky, J. W. Rosenboom, S. Ramalingam, L. Sriramajayam and J. Bartram, *et al.*, Public health performance of sanitation technologies in Tamil Nadu, India: Initial perspectives based on E. coli release, *Int. J. Hyg. Environ. Health*, 2022, **243**, 113987.

13 K. Andersson, S. Dickin and A. Rosemarin, Towards "Sustainable" Sanitation: Challenges and Opportunities in Urban Areas, *Sustainability*, 2016, **8**(12), 1289.

14 F. Mills, J. Willetts, B. Evans, N. Carrard and J. Kohlitz, Costs, Climate and Contamination: Three Drivers for Citywide Sanitation Investment Decisions, *Front. Environ. Sci.*, 2020, **8**, 130.

15 S. Dasgupta, N. Agarwal, S. Dasgupta and N. Agarwal, *Environmental Management - Pollution, Habitat, Ecology, and Sustainability*, IntechOpen, 2021.

16 F. Brikké, in *Operation and maintenance of rural water supply and sanitation systems: a training package for managers and planners*, 2000, Available from: https://www.semanticscholar.org/paper/Operation-and-maintenance-of-rural-water-supply-and-Brikk%C3%A9/5bddeb66ba36b51124a7248b63d6adbfb140b2d5.

17 E. Armstrong-Mensah, N. Laryes and M. Dotse, *Operation and Maintenance, Women What Role?*, 1996.

18 C. J. Pu, P. Patel, G. Hornsby, G. L. Darmstadt and J. Davis, Necessary conditions for sustainable water and sanitation service delivery in schools: A systematic review, *PLoS One*, 2022, **17**(7), e0270847.

19 J. Kaminsky and A. Javernick-Will, in *Causes for Sustainable Maintenance and Operation of On-Site Sanitation Systems*, American Society of Civil Engineers, 2012, [cited 2025 Feb 5], pp. 2270–2279, Available from: https://ascelibrary.org/doi/10.1061/9780784412329.228.

20 R. Cronk and J. Bartram, Factors Influencing Water System Functionality in Nigeria and Tanzania: A Regression and Bayesian Network Analysis, *Environ. Sci. Technol.*, 2017, **51**(19), 11336–11345.

21 M. B. Fisher, K. F. Shields, T. U. Chan, E. Christenson, R. D. Cronk and H. Leker, *et al.*, Understanding handpump sustainability: Determinants of rural water source functionality in the Greater Afram Plains region of Ghana, *Water Resour. Res.*, 2015, **51**(10), 8431–8449.

22 R. Giné-Garriga, D. Requejo, J. L. Molina and A. Pérez-Foguet, A novel planning approach for the water, sanitation and hygiene (WaSH) sector: The use of object-oriented bayesian networks, *Environ. Model. Softw.*, 2018, **103**, 1–15.

23 R. Goulding, N. Jayasuriya and E. Horan, A Bayesian network model to assess the public health risk associated with wet weather sewer overflows discharging into waterways, *Water Res.*, 2012, **46**(16), 4933–4940.

24 D. C. Hall and Q. B. Le, Use of Bayesian networks in predicting contamination of drinking water with E. coli in rural Vietnam, *Trans. R. Soc. Trop. Med. Hyg.*, 2017, **111**(6), 270–277.

25 R. E. Mulhern, A. Kondash, E. Norman, J. Johnson, K. Levine and A. McWilliams, *et al.*, Improved Decision Making for Water Lead Testing in U.S. Child Care Facilities Using Machine-Learned Bayesian Networks, *Environ. Sci. Technol.*, 2023, **57**(46), 17959–17970.

26 T. D. Phan, J. C. R. Smart, B. Stewart-Koster, O. Sahin, W. L. Hadwen and L. T. Dinh, *et al.*, Applications of Bayesian Networks as Decision Support Tools for Water Resource Management under Climate Change and Socio-Economic Stressors: A Critical Appraisal, *Water*, 2019, **11**(12), 2642.

27 T. D. Phan, J. C. R. Smart, O. Sahin, B. Stewart-Koster, W. L. Hadwen and S. J. Capon, Identifying and prioritising adaptation options for a coastal freshwater supply and demand system under climatic and non-climatic changes, *Reg. Environ. Change*, 2020, **20**(3), 88.

28 H. M. Semakula, S. Liang, P. I. Mukwaya, F. Mugagga, D. Nseka and H. Wasswa, *et al.*, Bayesian belief network modelling approach for predicting and ranking risk factors for malaria infections among children under 5 years in refugee settlements in Uganda, *Malar. J.*, 2023, **22**(1), 297.

29 R. Mulhern, J. Roostaei, S. Schwetschenau, T. Pruthi, C. Campbell and J. MacDonald Gibson, A new approach to a legacy concern: Evaluating machine-learned Bayesian networks to predict childhood lead exposure risk from community water systems, *Environ. Res.*, 2022, **204**, 112146.

30 M. Garshasbi, G. Kabir and S. Dutta, Stormwater Infrastructure Resilience Assessment against Seismic Hazard

Using Bayesian Belief Network, *Int. J. Environ. Res. Public Health*, 2023, **20**(16), 6593.

31 T. Chan, M. C. MacDonald, A. Kearton, M. Elliott, K. F. Shields and B. Powell, *et al.* Climate adaptation for rural water and sanitation systems in the Solomon Islands: A community scale systems model for decision support, *Sci. Total Environ.*, 2020, **714**, 136681.

32 M. Moffa, R. Cronk, L. Fleming and J. B. Tidwell, Measuring household hygiene access and handwashing behaviors: Findings from 14 low- and middle-income countries, *Int. J. Hyg. Environ. Health*, 2021, **237**, 113810.

33 P. J. Ward, H. C. Winsemius, S. Kuzma, M. F. P. Bierkens, A. Bouwman and H. D. Moel, *et al.*, Aqueduct Floods Methodology, 2020, Available from: https://www.wri.org/research/aqueduct-floods-methodology.

34 S. H. Chen and C. A. Pollino, Good practice in Bayesian network modelling, *Environ. Model. Softw.*, 2012, **37**, 134–145.

35 R. D. Shachter, Evaluating Influence Diagrams, *Operations Research*, 1986, **34**(6), 871–882.

36 World Health Organization, *Guidelines on sanitation and health*, World Health Organization, Geneva, 2018.

37 Norsys Software Corp., *Bayesian Network Software*, 2007.

38 S. Conrady and L. Jouffe, *Bayesian Networks & BayesiaLab - A Practical Introduction for Researchers*, 2015.

39 J. V. Carter, J. Pan, S. N. Rai and S. Galandiuk, ROC-ing along: Evaluation and interpretation of receiver operating characteristic curves, *Surgery*, 2016, **159**(6), 1638–1645.

40 J. A. Hanley and B. J. McNeil, The meaning and use of the area under a receiver operating characteristic (ROC) curve, *Radiology*, 1982, **143**(1), 29–36.

41 A. Peal, B. Evans, S. Ahilan, R. Ban, I. Blackett and P. Hawkins, *et al.*, Estimating Safely Managed Sanitation in Urban Areas; Lessons Learned From a Global Implementation of Excreta-Flow Diagrams, *Front. Environ. Sci.*, 2020, **8**, DOI: 10.3389/fenvs.2020.00001.

42 D. G. Toll, Z. Abedin, J. Buma, Y. Cui, A. S. Osman and K. K. Phoon, The impact of changes in the water table and soil moisture on structural stability of buildings and foundation systems: Systematic review CEE10-005 (SR90), 2012, Available from: https://durham-repository.worktribe.com/output/1636508/the-impact-of-changes-in-the-water-table-and-soil-moisture-on-structural-stability-of-buildings-and-foundation-systems-systematic-review-cee10-005-sr90.

43 Z. Sakas, E. A. Uwah, R. K. Bhattrai, J. V. Garn, K. H. Gc and A. Mutta, *et al.*, Assessing Sustainability Factors for Rural Household Sanitation Coverage in Bhutan, Kenya, Nepal, and Zambia: A Qualitative Analysis, *Glob. Health Sci. Pract.*, 2022, **10**(6), e2100724.

44 S. Nelson, D. Drabarek, A. Jenkins, J. Negin and S. Abimbola, How community participation in water and sanitation interventions impacts human health, WASH infrastructure and service longevity in low-income and middle-income countries: a realist review, *BMJ Open*, 2021, **11**(12), e053320.

45 T. Sainati, F. Zakaria, G. Locatelli, P. A. Sleigh and B. Evans, Understanding the costs of urban sanitation: towards a standard costing model, *J. Water Sanit. Hyg. Dev.*, 2020, **10**(4), 642–658.

46 N. Carrard, J. Willetts, A. Kome and R. Munankami, Sustainable cost recovery principles can drive equitable, ongoing funding of critical urban sanitation services, *npj Clean Water*, 2024, **7**(1), 1–4.

47 P. Kumar, N. Hasan and R. Rajak, Socio-economic disparities in the utilization of improved sanitation facilities among Indian households, *Sci. Rep.*, 2024, **14**(1), 31659.

48 J. P. Borges Pedro, C. A. da S. Oliveira, S. C. R. B. de Lima and M. von Sperling, A review of sanitation technologies for flood-prone areas, *J. Water Sanit. Hyg. Dev.*, 2020, **10**(3), 397–412.

49 A. Davis, Sustainable Sanitation Systems: Understanding Priorities, Processes, and Pathways to Success, *Ph.D thesis*, University of Colorado at Boulder, USA, Colorado, 2019.

50 S. Lebu, R. Gyimah, E. Nandoya, J. Brown, A. Salzberg and M. Manga, Assessment of sanitation infrastructure resilience to extreme rainfall and flooding: Evidence from an informal settlement in Kenya, *J. Environ. Manage.*, 2024, **354**, 120264.

51 B. Bakare, Scientific and management support for ventilated improved pit latrines (VIP) sludge content, 2014, Available from: https://www.academia.edu/97137571/Scientific_and_management_support_for_ventilated_improved_pit_latrines_VIP_sludge_content.

52 M. W. Jenkins, O. Cumming and S. Cairncross, Pit Latrine Emptying Behavior and Demand for Sanitation Services in Dar Es Salaam, Tanzania, *Int. J. Environ. Res. Public Health*, 2015, **12**(3), 2588–2611.

53 S. Simiyu, Determinants of usage of communal sanitation facilities in informal settlements of Kisumu, Kenya, *Environ. Urban.*, 2016, **28**(1), 241–258.

54 L. Hyde-Smith, Z. Zhan, K. Roelich, A. Mdee and B. Evans, Climate Change Impacts on Urban Sanitation: A Systematic Review and Failure Mode Analysis, *Environ. Sci. Technol.*, 2022, **56**(9), 5306–5321.

55 K. Conaway, S. Lebu, K. Heilferty, A. Salzberg and M. Manga, On-site sanitation system emptying practices and influential factors in Asian low- and middle-income countries: A systematic review, *Hyg. Environ. Heal. Adv.*, 2023, **6**, 100050.

56 G. Howard, R. Calow, A. Macdonald and J. Bartram, Climate Change and Water and Sanitation: Likely Impacts and Emerging Trends for Action, *Annu. Rev. Environ. Resour.*, 2016, **41**(1), 253–276.

57 P. M. Nyenje, J. W. Foppen, R. Kulabako, A. Muwanga and S. Uhlenbrook, Nutrient pollution in shallow aquifers underlying pit latrines and domestic solid waste dumps in urban slums, *J. Environ. Manage.*, 2013, **122**, 15–24.

58 J. O. Back, M. O. Rivett, L. B. Hinz, N. Mackay, G. J. Wanangwa and O. L. Phiri, *et al.*, Risk assessment to groundwater of pit latrine rural sanitation policy in developing country settings, *Sci. Total Environ.*, 2018, **613–614**, 592–610.

59 M. Mbae, P. Hansen, C. Way, F. Mills, J. Willetts and T. Foster, *et al.*, Onsite sanitation systems and contamination of groundwater: A systematic review of the evidence for risk using the source-pathway-receptor model, *PLOS Water*, 2024, **3**(7), e0000167.

60 J. P. Graham and M. L. Polizzotto, Pit Latrines and Their Impacts on Groundwater Quality: A Systematic Review, *Environ. Health Perspect.*, 2013, **121**(5), 521–530.

61 R. Gyimah, S. Lebu, I. Owusu-Frimpong, S. Semiyaga, A. Salzberg and M. Manga, Effluents from septic systems and impact on groundwater contamination: a systematic review, *Environ. Sci. Pollut. Res. Int.*, 2024, **31**(54), 62655–62675.

62 A. J. Pickering, H. Djebbari, C. Lopez, M. Coulibaly and M. L. Alzua, Effect of a community-led sanitation intervention on child diarrhoea and child growth in rural Mali: a cluster-randomised controlled trial, *Lancet Glob. Health*, 2015, **3**(11), e701–e711.

