

Leveraging satellite data and machine learning to quantify rooftop rainwater harvesting reliability and tank requirements for schools and health care facilities in Uganda

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ABSTRACT

Many schools and health facilities in Uganda lack a reliable water supply, yet most have roofs that could collect rain. For 41,592 facilities (32,881 schools and 8,711 health facilities), we estimated how much water their roofs can supply, how large a tank each one needs, and how often that supply fails. Roof areas came from AI-derived building footprints (Google Open Buildings v3) and daily rainfall for 1981 to 2025 from CHIRPS. A daily yield-after-spillage tank model gave the supply available on 90% of days and the smallest tank that meets each facility's demand on 90% of days. On a standard 200 m² roof, a 10 m³ tank supplied a median of 359 litres per day on 90% of days, from 255 L in the Northern region to 411 L in the Eastern region; at the same annual rainfall, Northern facilities received about 40% less because their rain falls in one long season. With mapped roofs, 77.1% of schools and 62.2% of health facilities could reach the target with a tank of 200 m³ or less, and among these the median school needed 39.5 m³ and the median health facility 5.0 m³. The school share ranged from 42.3% to 92.8% across enrolment scenarios and fell to 44.1% if only buildings within 60 m are connected and to 37.8% if only 30% of the mapped roof feeds the tank. A machine-learning model trained on the simulations predicted the required tank within 25% for 97.0% of facilities in spatial cross-validation, against 8.3% for the dry-period rule of thumb. With a 20% margin its tanks met the target at 97.5% of facilities, but at only 74.5% when the nearest training data were at least 110 km away, where the rule's larger tanks were more dependable. Reliability rose slightly over 1981 to 2025, with a significant trend at 15.1% of facilities. A retrospective seasonal analysis found useful skill only for September to November, coming from tank storage and recent rain rather than El Niño or Indian Ocean Dipole indices. The results are screening estimates that need confirmation on site; the code and data are released openly.

Introduction

Schools and health facilities need water every day. Pupils need it for drinking, handwashing and toilets, and health facilities need it for infection control, deliveries and cleaning. Yet globally 29% of schools had no basic drinking water service in 2021, affecting 546 million pupils [1], and studies in Ugandan towns show large gaps in school water services [2]. Health care facilities face similar gaps [3]. When water runs out, pupils walk to collect it, girls miss school during menstruation, and health workers cannot keep basic hygiene.

Rooftop rainwater harvesting is one of the cheapest ways to close this gap. Most facilities already have iron-sheet roofs, and Uganda receives between about 640 and 2,430 mm of rain a year at the facilities studied here, with a median of about 1,280 mm. Government and partners already install tanks at schools and health centres, but tank sizes are often chosen by rule of thumb or budget rather than by roof area, local rainfall pattern and number of users. A tank that is too small runs dry in the dry season, and one that is too large uses money that could have bought a tank elsewhere.

Three gaps limit better planning. First, there is no national, facility-level estimate of how much water each roof can supply and how reliable it is. Past studies looked at single sites or used monthly rainfall, which hides the dry spells that empty tanks [4]. Second, roof areas were not known at scale until AI-derived building footprints became available [5]. Third, tank supply changes from year to year with the climate, and it is not known whether a poor tank season can be predicted before it starts, for example from the links between East African rainfall, El Niño and the Indian Ocean Dipole [6,7].

Most studies of rooftop harvesting in East Africa look at one site or one town. In western Uganda, Kisakye et al. [8] modelled systems in Kabarole District and found that climate change will cut reliability most in the March to May season. In Ethiopia, Taffere et al. [9] analysed reliability in semi-arid Mekelle, and Adugna et al. [10] assessed 320 large public institutions in Addis Ababa, noting that uneven rainfall makes tank size the critical choice. Parker et al. [11] studied what rainwater tanks cost in East Africa, a key input for any sizing decision.

The tools for a national study now exist. Daily behavioural models are the accepted way to size tanks [4]. AI-derived building footprints give roof outlines for most buildings across Africa [5]. CHIRPS provides daily rainfall since 1981; it performs well at ten-day and monthly scales in eastern Africa, though less well day by day [12,13]. To our knowledge, no study has combined these to size tanks and assess seasonal failure risk for every school and health facility in a country.

This study fills that gap for every mapped school and health facility in Uganda. Its objectives are to: (1) estimate the roof catchment of each facility from AI-derived building footprints; (2) model daily tank behaviour over 45 years and report the water supplied on 90% of days for standard tank sizes; (3) find the smallest tank that lets each facility meet its demand on 90% of days, and flag facilities where no tank up to 200 m³ is enough; (4) train a machine-learning model that predicts the required tank from simple roof, demand and climate features, so planners can size tanks without running a daily simulation; (5) test whether reliability has changed between 1981 and 2025; and (6) test whether machine learning can warn of poor tank seasons before they start, and whether climate indices add to that warning.

Materials and methods

Study area

Uganda lies on the equator in East Africa, between about 1.5°S and 4.2°N and 29.5°E and 35°E. Most of the country is a plateau at 900 to 1,500 m, with Lake Victoria in the south and highlands on the Kenyan and Congolese borders. Around Lake Victoria and in much of the Centre, East and West, rain falls in two seasons, March to May and September to November. In the North, the two seasons merge into one long wet season from about April to October, followed by a long dry season from about December to March. A tank can refill twice a year under two seasons, but must last through one long dry spell under a single season.

Data

All data are public (Table 1). The study used no human or animal subjects.

Table 1. Data sources used in this study.

Data	Source	Coverage	Used for
Health facility locations	Maina et al. [14], Ministry of Health 2018 list, OpenStreetMap	11,950 records, 8,711 with usable locations	Facility points and level (HC II to hospital)
School locations	OpenStreetMap education features	32,881 after removing duplicates	Facility points and type
Building footprints	Google Open Buildings v3 [5], confidence 0.75 or more	Whole country	Roof catchment area
Daily rainfall	CHIRPS v2.0 [12], 0.05° grid	1981 to 2025, 4,890 pixels	Tank model input
El Niño index	Niño 3.4 SST anomaly, NOAA PSL	Monthly, 1981 to 2026	Early-warning feature
Indian Ocean Dipole	Dipole Mode Index, NOAA PSL	Monthly, 1981 to 2026	Early-warning feature
Boundaries	Uganda admin levels 1 and 2	Regions and districts	Mapping and summaries

Health facilities were merged from three sources. The Ministry of Health 2018 list was parsed from PDF and cleaned, records were matched across sources by name and distance, and only records with a reliable location (8,711) were kept. Schools were taken from OpenStreetMap and duplicates within 150 m with similar names were removed. Each facility got a search radius for roofs: 100 m for health centres, 200 m for hospitals, and 150 m for schools, or the mapped campus radius up to 400 m. CHIRPS daily values were sampled at the centre of each 0.05° pixel holding at least one facility (4,890 pixels) in Google Earth Engine, and each facility used the rainfall of its own pixel.

Roof catchment area

Building polygons from Open Buildings v3 with confidence 0.75 or more were joined to each facility in Google Earth Engine, keeping every polygon within the search radius. For each facility we stored the total roof area within the radius and the roof area within 60 m of the facility point. In the base case, schools use the total roof area, because classrooms and dormitories spread across a campus, and health facilities use the 60 m core, to avoid counting nearby homes and shops. The footprints show buildings, not which buildings belong to the facility or have gutters connected to a tank, so roof area is an estimate of the possible catchment. Because the school choice may include neighbouring buildings, the sensitivity analysis also limits schools to the 60 m core.

Daily tank model

Each facility's tank was simulated day by day from 1 January 1981 to 31 December 2025 (16,436 days) with the yield-after-spillage (YAS) rule [4]. Inflow on day t is

$$Q_t = C \cdot A \cdot \max(P_t - L, 0) / 1000 \quad (1)$$

where Q_t is the inflow on day t (m^3), A is roof area (m^2), P_t is daily rain (mm), the factor $1/1000$ converts $\text{mm} \times \text{m}^2$ to m^3 , $C = 0.8$ is the runoff coefficient for iron roofs and gutters, and $L = 0.5$ mm is lost to first flush and wetting on each rain day. Under YAS, water is drawn only from what was stored at the start of the day, and spillage is computed before the draw:

$$Y_t = \min(D, S_{t-1}), S_t = \min(S_{t-1} + Q_t, K) - Y_t \quad (2)$$

where Y_t is the water supplied on day t (m^3), D is daily demand (m^3 per day), K is tank capacity (m^3) and S_t is the storage at the end of day t (m^3). This is the more conservative of the two standard rules, because rain that falls on a day cannot be used until the next day. A day counts as met only when the full demand is supplied, and the tank starts empty.

Demand

School demand follows the WHO standard of 5 litres per pupil per day for day schools and 20 litres for boarding schools [15]. Health facility demand follows WHO guidance for health care settings, which sets minimums of 5 litres per outpatient consultation and 40 to 60 litres per inpatient per day [16]. We used 10 litres per outpatient, above the minimum to allow for cleaning, and 50 litres per inpatient or delivery (Table 2). Enrolment and patient numbers are not known for every facility, so we used typical values. Uganda had 8.66 million primary pupils in 2016 with an average of 56 pupils per classroom [17], so a single-stream school with seven classes holds about 390 pupils; our 600 pupils represents a medium to large school, and the sensitivity analysis halves and doubles it. The supply results (litres per day and pupils served) do not depend on these assumptions.

Table 2. Daily water demand assumed for each facility type.

Facility type	Assumed users	Demand (L/day)
Primary or secondary school	600 pupils $\times$ 5 L	3,000 (12,000 if boarding)
College	400 students $\times$ 5 L	2,000
University	2,000 students $\times$ 5 L	10,000
Kindergarten	80 pupils $\times$ 5 L	400
Health Centre II	40 outpatients $\times$ 10 L	400
Health Centre III	80 outpatients $\times$ 10 L + 10 inpatients $\times$ 50 L	1,300
Health Centre IV	150 outpatients $\times$ 10 L + 30 inpatients $\times$ 50 L	3,000
Hospital	300 outpatients $\times$ 10 L + 100 inpatients $\times$ 50 L	8,000

Reliability and tank sizing

We used 90% of days as the planning target. This is a design scenario, not a full service: it still leaves about 36 days a year, on average, when the full demand is not met (the tank may be low rather than empty) and another source or rationing is needed. For each facility we computed: (1) the largest daily demand that a 5, 10 or 20 m³ tank meets on 90% of days, found by bisection; (2) the smallest tank between 0.5 and 200 m³ that meets the facility's demand on 80% and on 90% of days, found by bisection on a log scale and rounded up to 0.5 m³; and (3) a flag for facilities where even a 200 m³ tank cannot reach the target. We call these "not reachable within 200 m³" rather than roof-limited, because a larger tank could help some of them. To separate the two cases, we reran the flagged facilities with an effectively unlimited tank (10⁹ m³). We also used a simple bound: meeting the full demand D on 90% of N days needs at least $0.9 \cdot N \cdot D$ of water, and no tank can supply more than the total inflow, so a facility whose total inflow over the record is below $0.9 \cdot N \cdot D$ cannot reach the target with any tank. Both tests refer to the 1981 to 2025 rainfall sequence with a tank that starts empty; they do not prove what would happen under every possible future rainfall sequence. Under the boarding scenario, every school except kindergartens was run at four times its day-school demand.

Sensitivity analysis

Each key assumption was changed one at a time and the tank sizing was rerun for all facilities: school enrolment $\times 0.5$ and $\times 2$; health demand $\times 0.5$ and $\times 2$; runoff coefficient 0.7 and 0.9; first-flush loss 0 and 1 mm; school catchment limited to roofs within 60 m; only 50% or 30% of the mapped roof connected to the tank, for all facilities, because many buildings have gutters on one side only or none; and all daily rainfall multiplied by $1/0.82$ (about 1.22), which restores the gauge total found in the

validation. This last scenario tests rainfall amount only; errors in the timing of rain days and dry spells were not tested.

Machine-learning tank sizing

The daily simulation needs 45 years of daily rain and many model runs per facility. To give planners a fast tool, and to learn which factors drive tank size, we trained gradient-boosted trees (XGBoost [18]) to reproduce the simulation. So that the model covers a wide range of demands, not just the eight standard levels, each facility was given a random demand drawn log-uniformly between 100 and 20,000 litres per day, and the simulation was rerun to find its flag and its tank for 90% of days. The model should not be used outside this range. The features were roof catchment, daily demand, demand per square metre of roof, the ratio of mean annual harvest to annual demand, facility type, and seven rainfall descriptors per CHIRPS pixel: mean annual rain, 10th percentile annual rain, inter-annual coefficient of variation, wet days per year (1 mm or more), mean longest dry spell per year, the Walsh seasonality index, and the share of rain in the wettest three months.

A classifier predicted the flag and a regressor predicted the logarithm of tank size for facilities whose target is reachable (28,437). Settings were fixed in advance and not tuned (regressor: 600 trees, depth 6, learning rate 0.05, subsample 0.8, column sample 0.8, minimum child weight 5, L2 penalty 2; classifier: 400 trees, depth 5; random seed 42). Both were tested with spatial block cross-validation [19]: facilities were grouped into 1° by 1° blocks and split into five folds by block. Because facilities in neighbouring blocks can be close together, we repeated the test with a buffer that removed from training every facility in a block touching a test block, so training and test facilities were at least about 110 km apart. The fold assignments are released with the code. The baselines were two textbook heuristics: a facility is flagged if its mean annual harvest is less than its annual demand (a rule of thumb, not a proof of feasibility), and the tank equals daily demand multiplied by the mean longest dry spell (the dry-period method). Because an error in tank size does not show whether the design target is met, we also installed each predicted tank in the daily model and recorded the reliability it achieved. After seeing that unbiased predictions reached the target only about half the time, we also tested fixed safety margins of 10% and 20%. These round values were chosen after that first result, not tuned, and were applied in both the standard and the buffered validation. SHAP values [20] from a model fitted to all data showed how each feature drives the predictions. The same model was also trained on the standard-demand results as a check.

Change over time

Yearly reliability with a 10 m³ tank at standard demand was computed for every facility for each year from 1981 to 2025. We report the change between 1981 to 1995 and 2011 to 2025, the Theil-Sen slope [21], and the Mann-Kendall test [22] for a monotonic trend. Because 41,592 tests were run, p-values were adjusted with the Benjamini-Hochberg false discovery rate at 5% [23].

Machine-learning early warning

The aim was to tell a facility, at the start of a three-month season, whether its tank is likely to have a worse season than usual. Each facility was given a 10 m³ tank and a demand equal to what it supplies on 80% of days over the record, so all systems are equally well designed on average. For every facility and season (DJF, MAM, JJA, SON), the target was the share of days the tank failed, and the features, all known on the first day of the season, were water stored in the tank, rain in the previous 30 and 90 days, Niño 3.4 and the Dipole Mode Index averaged over the two months before the season, roof area, demand per square metre of roof, mean annual rain, latitude and longitude. Facilities with less than 20 m² of roof (4.5%) were left out of this step.

The baseline was climatology, the facility's own mean failure share for that season in the training years. Because climate indices are shared by all facilities in a year, a flexible model can memorise years instead of learning the climate signal, so the models predicted the anomaly from climatology with Ridge regression and a strongly regularised XGBoost model, fitted for each season. This is a retrospective experiment on a fixed system: the demand was set from the full 45-year record, including the held-out years, so the results show how well a season can be ranked against climatology, not the exact skill of a live forecast. Models were tested with leave-years-out cross-validation: the 45 years were split into five blocks of about nine years, each held out in turn, with climatology recomputed from the training years only. We report the skill score against climatology (1 minus the ratio of mean squared errors), the ROC AUC for a bad season, defined as a failure share at least 0.15 above the facility's climatology, and the range across the five held-out blocks. To measure what El Niño and the Indian Ocean Dipole add, the same models were refitted without the two indices.

Validation

For roofs, a random sample of 1,200 facilities was drawn and roof area was recomputed from a second, independent dataset, the Microsoft building footprints for Uganda [24], within the same radius. This checks agreement between two footprint products; it does not check which buildings belong to a facility. For rainfall, daily CHIRPS values were compared with gauge records from the NOAA Global Summary of the Day [25] at Ugandan synoptic stations, 2001 to 2025, using only complete 24-hour reports. Because daily gauge records are patchy, the comparison used matched days, ten-day totals with at least 8 reported days, and rain-day detection at 1 mm. The rainfall bias is the total CHIRPS rain divided by the total gauge rain over all matched days.

Results

Results cover all 41,592 facilities. Median roof area was 2,240 m² for schools and 880 m² for health facilities (60 m core), and 4.5% of facilities had less than 20 m² of mapped roof.

Validation

Microsoft footprints cover only part of Uganda: of the 1,200 sampled facilities, 94 had buildings in both datasets. Where both exist, they agreed closely (correlation of log roof area 0.95 for schools and 0.94 for health facilities). Open Buildings gave about 10% more roof area than Microsoft at the median, and 81% of schools fell within a factor of 1.5. Open Buildings also detected buildings at most of the sampled facilities where Microsoft had none.

Across 12,713 matched station-days at 8 stations (Arua, Gulu, Masindi, Soroti, Kasese, Jinja, Tororo and Entebbe), CHIRPS detected 61% of gauge rain days, and 41% of CHIRPS rain days had no gauge rain. Ten-day totals correlated at 0.52 (248 dekads). Total CHIRPS rain on matched days was 0.82 of the gauge total, 18% lower. Modest daily agreement is expected in eastern Africa [13]. The lower totals suggest our supplies may be underestimated, but the errors in rain-day timing could act in either direction.

Reliable supply on a standard roof

On a 200 m² roof, a 10 m³ tank supplied a median of 359 litres per day on 90% of days (Table 3, Fig 1). The Northern region had the lowest supply and the Eastern region the highest.

Table 3. Median supply on 90% of days for a standard 200 m² roof and a 10 m³ tank, by region.

Region	Median supply (L/day)
Eastern	411
Central	403
Western	343
Northern	255
Uganda	359

Water a 10 m³ tank supplies on 90% of days

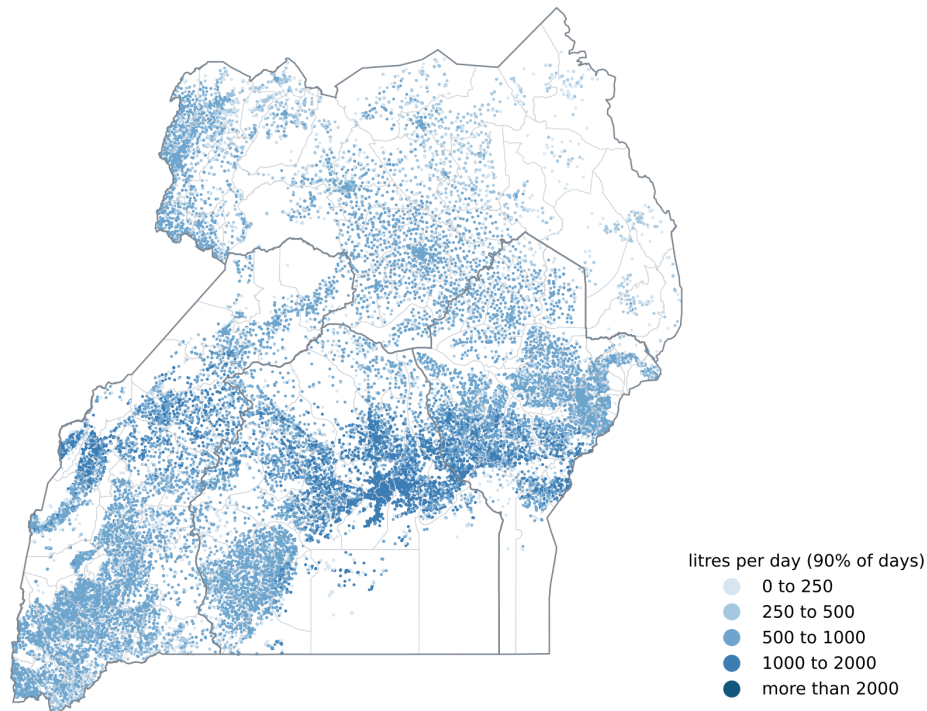


Fig 1. Water a 10 m³ tank supplies on 90% of days at each facility, using each facility's mapped roof area.

At the same annual rainfall, Northern facilities received about 40% less reliable supply than Central ones (Fig 2). With 1,200 to 1,400 mm of rain a year, a 200 m² roof and 10 m³ tank gave a median of 244 litres per day in the North against 407 in the Central region. The single long dry season in the North empties tanks, while two wet seasons refill them elsewhere.

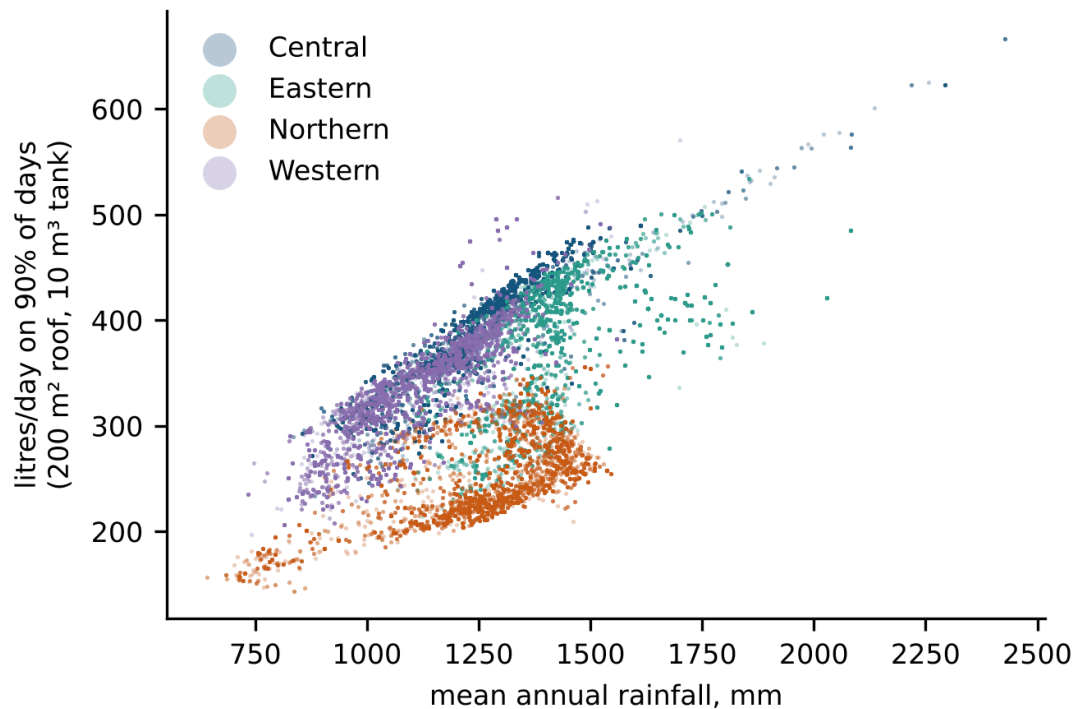


Fig 2. Mean annual rainfall against supply on 90% of days for a standard 200 m² roof and 10 m³ tank, by region. At the same rainfall, Northern facilities get less reliable water.

Tank sizes with mapped roofs

Nationally, 77.1% of schools and 62.2% of health facilities could meet their standard demand on 90% of days with a tank of 200 m³ or less (Table 4, Figs 3 and 4). Among facilities that reached the target, the median tank needed was 39.5 m³ for schools and 5.0 m³ for health facilities (24.5 and 3.0 m³ for 80% of days). With a 10 m³ tank, median reliability at standard demand was 0.56 for schools and 0.87 for health facilities, and a 10 m³ tank at the median school serves about 166 pupils at 5 litres each on 90% of days. Under the boarding scenario only 16.0% of schools could reach the target, and those that could needed a median tank of 114.5 m³.

Of the facilities that could not reach the target within 200 m³ (26.0%), 87.9% could not reach it even with unlimited storage over the 1981 to 2025 record, so their roof, or the assumed demand, is the limit. For 86.1% this follows directly from the water-balance bound, and the simulation agreed with the bound in every case. The other 12.1% (15.1% of flagged schools, 5.2% of flagged health facilities) could reach the target only with more than 200 m³ of storage. With a 200 m³ tank, the median flagged facility met its demand on 42% of days.

Table 4. Ability to meet standard demand on 90% of days with a tank of 200 m³ or less, and median tank size needed among facilities that reach the target, by region.

Region	Schools	Schools able (%)	Median school tank (m ³)	Boarding able (%)	Health facilities	Health able (%)	Median health tank (m ³)
Central	10,147	82.7	27.5	37.2	2,912	73.1	3.5
Eastern	6,974	85.7	41.5	13.9	1,864	62.8	4.5
Western	9,053	75.1	48.5	5.4	1,980	53.9	5.5
Northern	6,702	62.4	102.5	0.9	1,953	53.7	6.5
Uganda	32,881	77.1	39.5	16.0	8,711	62.2	5.0

Seven facilities fall just outside the regional boundaries and are counted only in the Uganda row. The median Northern school needed a 102.5 m³ tank, almost four times the Central figure.

Tank needed to meet daily demand on 90% of days

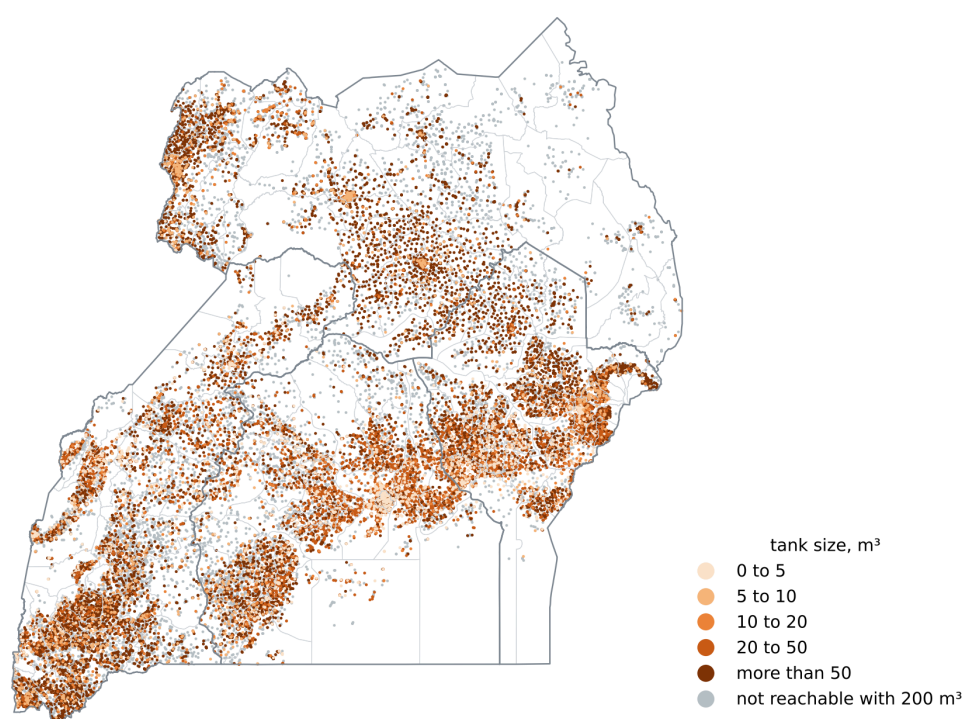


Fig 3. Tank size needed to meet standard demand on 90% of days. Facilities that cannot reach the target within 200 m³ are shown in grey.

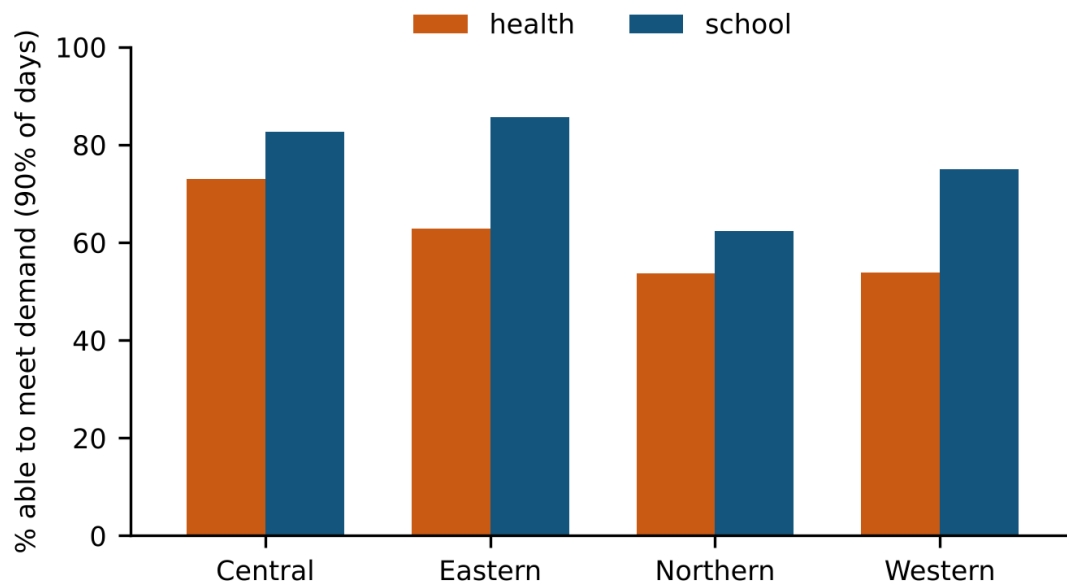


Fig 4. Share of facilities able to meet standard demand on 90% of days with a tank of 200 m³ or less, by region and facility type.

Fig 5 shows the model at work for two typical schools. The Central school refills in both wet seasons and runs short only in brief spells during each of its two dry seasons, while the Northern school, with less roof, needs a tank four times larger to carry it through one long dry season, and still runs short in the weeks before the rains return.

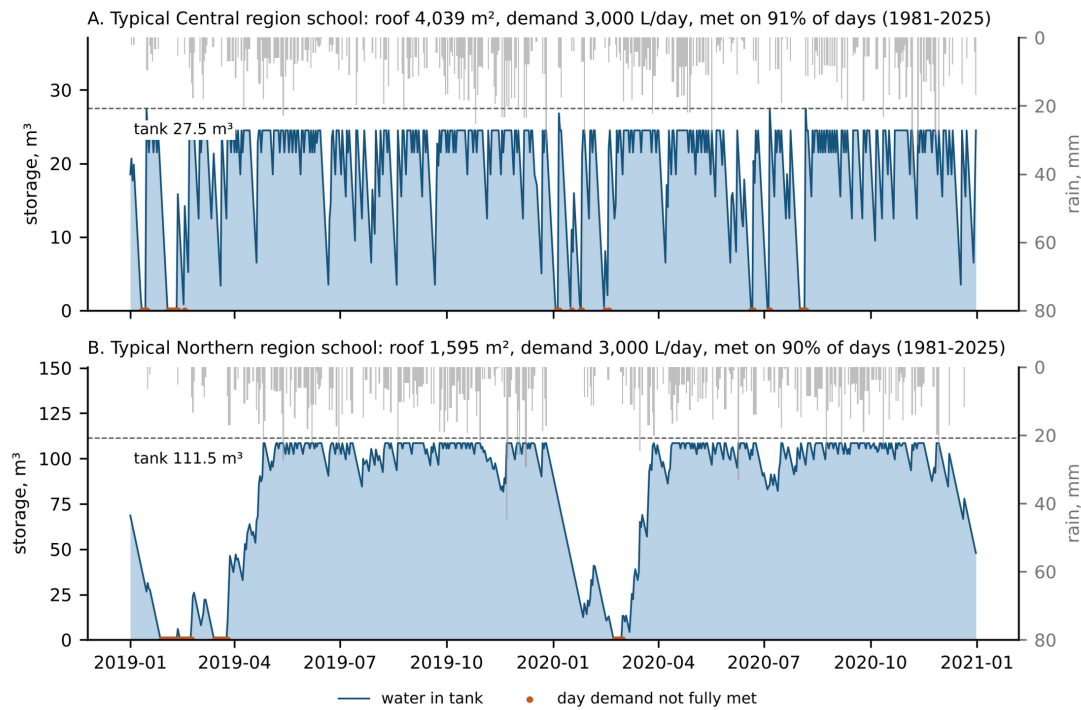


Fig 5. Daily tank storage in 2019 and 2020 for a typical Central (A) and Northern (B) region school (the school closest to its region's median roof area and median required tank), each with the tank the model recommends for 90% of days. Grey bars show daily rain (right axis) and orange dots mark days when the full demand was not met. Under the yield-after-spillage rule, storage after the day's draw stays at least one day's demand below the tank capacity (dashed line).

Sensitivity to assumptions

The share of schools able to meet demand depends strongly on the school assumptions (Table 5). Halving enrolment raised it to 92.8% and doubling it lowered it to 42.3%. Limiting school catchment to buildings within 60 m lowered it to 44.1%, with a median tank of 50 m³. Health results moved less: between 53.5% and 70.0% of health facilities could meet demand across the demand range. The runoff coefficient, first-flush loss and the rainfall amount each changed the shares by less than 6 percentage points. Restoring the gauge rainfall total raised the school share to 83.1%. Partial guttering mattered much more: if only half of the mapped roof feeds the tank, 52.4% of schools and 54.0% of health facilities could reach the target, and with 30% connected, 37.8% and 46.4%. The median tank among those that still reach the target hardly changes, because the facilities that drop out are the ones with the least roof per user. The national shares should therefore be read as a range that depends mainly on how many pupils a school has and how much of its roof is connected.

Table 5. One-at-a-time sensitivity of the main results. Tank sizes are medians among facilities that reach the target, before rounding up to 0.5 m³.

Scenario	Schools able (%)	Median school tank (m ³)	Health able (%)	Median health tank (m ³)
Base case	77.1	39.2	62.2	4.8
School enrolment $\times 0.5$	92.8	18.0	62.2	4.8
School enrolment $\times 2$	42.3	62.0	62.2	4.8
Health demand $\times 0.5$	77.1	39.2	70.0	2.4
Health demand $\times 2$	77.1	39.2	53.5	9.7
Runoff coefficient 0.7	72.8	41.0	60.8	4.8
Runoff coefficient 0.9	80.6	39.0	63.3	4.8
First-flush loss 0 mm	79.3	39.0	62.8	4.8
First-flush loss 1 mm	74.7	42.1	61.5	4.8
School roofs within 60 m only	44.1	50.4	62.2	4.8
Connected roof 50%	52.4	39.0	54.0	5.0
Connected roof 30%	37.8	36.0	46.4	5.2
Rainfall $\times 1.22$ (gauge total)	83.1	39.0	64.2	4.8

Machine-learning tank sizing

The machine-learning model reproduced the 45-year simulation closely on facilities in held-out blocks (Table 6, Fig 6). It predicted the required tank within 25% for 97.0% of facilities (range 91.4% to 99.6% across the five folds), against 8.3% for the dry-period rule, with a median error of 5.1% against 111%. For the flag, the annual water-balance heuristic already did well (accuracy 95.8%), and the model improved it to 99.3%; this means the model reproduces our label, which itself depends on the 200 m³ limit.

Installed in the daily model, the predicted tanks met their demand on a median of 90.1% of days, and 99.9% of them reached at least 85%, but only 55.5% reached the full 90% target, because an unbiased prediction is too small about half the time. Adding a 10% margin raised this to 89.5% and a 20% margin to 97.5%. The dry-period rule reached the target at 89.7% of facilities, but it over-sized most tanks and needed 1.00 million m³ of storage in total, against 0.88 million m³ for the model with a 20% margin, 12% less, while still leaving 0.9% of facilities below 80%.

With the 110 km buffer, accuracy fell to 70.6% within 25% overall, and the predicted tanks reached the target at 51.8% of facilities, 65.4% with a 10% margin and 74.5% with a 20% margin (1.4% below 80% of days). The rule needs no training data, so on these same facilities its results do not change: 8.3% within 25% and 89.7% reaching the target, using 1.00 million m³ of storage against 0.79 million m³ for the model with a 20% margin. Far from its training data, the model therefore saves storage but meets the target less often than the rule; there, the rule's larger tanks, or a larger margin, are the safer choice. The drop depended on how much training data was left: in the fold that kept 13,497 training facilities, 98.2% were still within 25%, but in the fold that kept only 87, 30.7% were. The model therefore transfers well across distance

when similar roofs and climates are in the training data, and should not be used for climates it has not seen. Trained on the standard-demand results instead, the model gave similar accuracy (96.8% within 25%, against 14.3% for the rule).

Table 6. Machine-learning tank sizing against textbook rules (spatial block cross-validation, random demands of 100 to 20,000 L/day).

Task	Measure	Machine learning	Rule
Target reachable within 200 m ³ (41,592 facilities)	Accuracy	99.3%	95.8%
	ROC AUC	1.00	0.99
Tank for 90% of days (28,437 facilities)	R ² of log tank size	0.996	0.77
	Median absolute error	5.1%	111%
	Within 25% of simulated size	97.0%	8.3%
	Within 25%, 110 km buffer	70.6%	8.3% (needs no training data)
	Under-sized by more than 25%	1.4%	7.0%
Achieved reliability with the predicted tank	Reaching 90% of days	55.5% (97.5% with a 20% margin)	89.7%
	Below 80% of days	0.0%	0.9%
	Total storage (million m ³)	0.74 (0.88 with a 20% margin)	1.00
	Reaching 90% of days, 110 km buffer	51.8% (74.5% with a 20% margin)	89.7%
	Total storage, 110 km buffer (million m ³)	0.66 (0.79 with a 20% margin)	1.00

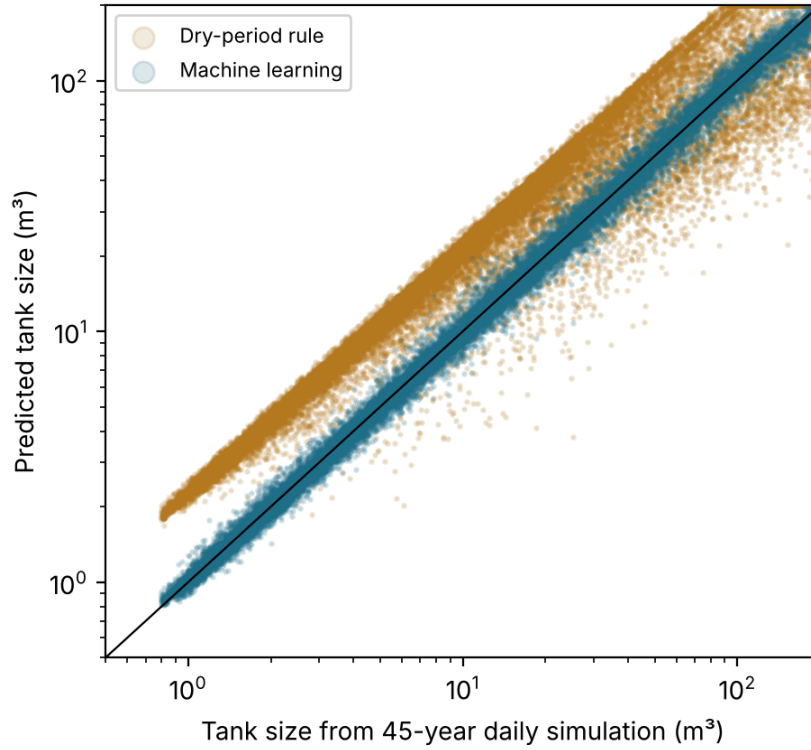


Fig 6. Tank size predicted by machine learning and by the dry-period rule against the size from the 45-year daily simulation (held-out spatial blocks, log scales).

SHAP values showed that tank size is driven mainly by daily demand, then by demand per square metre of roof, roof area, the longest dry spell and the ratio of annual harvest to demand (Fig 7). Mean annual rainfall had a small direct effect, but this does not mean rain amount is unimportant: it already enters the model through the harvest-to-demand ratio. Among the rainfall descriptors, the longest dry spell and seasonality mattered most, which agrees with Fig 2.

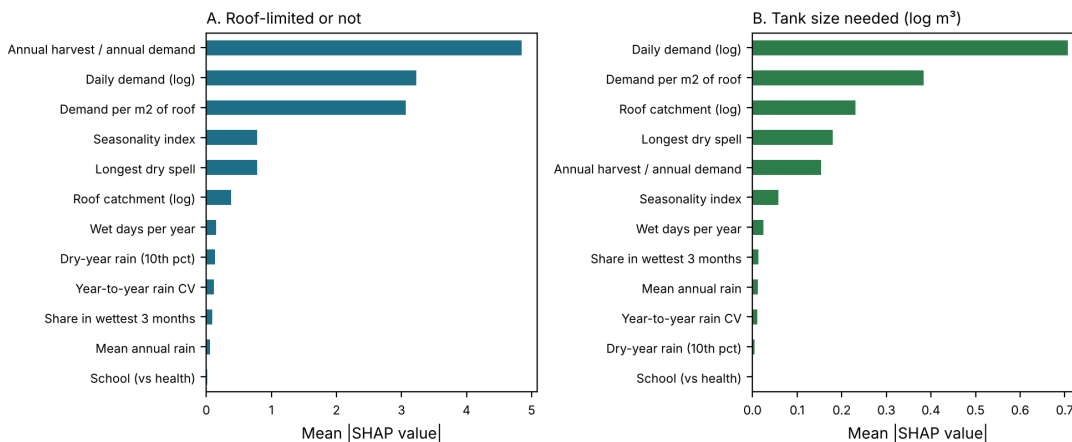


Fig 7. Mean absolute SHAP values for (A) the classifier for reaching the target within 200 m³ and (B) the tank-size regressor.

Change over time

Reliability with a 10 m³ tank rose over the record. Between 1981 to 1995 and 2011 to 2025 it rose by more than 2 percentage points at 57.8% of facilities and by more than 5 points at 9.3%, mostly in the East, the Centre and around Lake Victoria, and fell by more than 2 points at only 0.6% (largest fall 7.6 points; Fig 8). The median Theil-Sen slope was +0.7 percentage points per decade. After false discovery rate control, the rising trend was significant at 15.1% of facilities (34.1% in the Eastern region, 0.8% in the Western region), and a falling trend at 0.6%.

Reliability 2011-2025 minus 1981-1995 (10 m³ tank, standard demand)

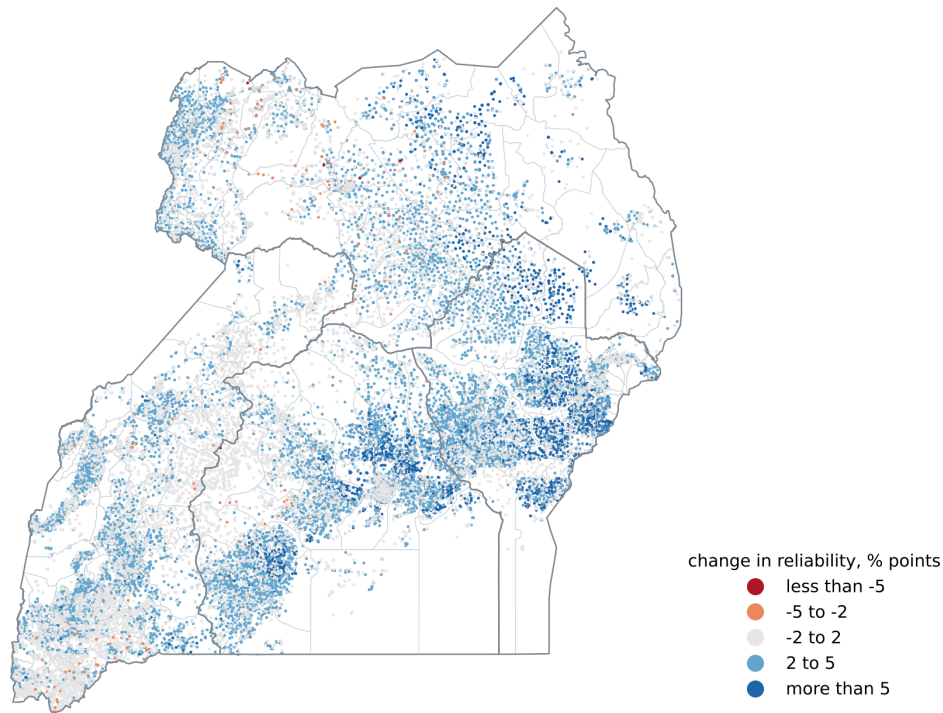


Fig 8. Change in reliability between 1981 to 1995 and 2011 to 2025, in percentage points (10 m³ tank, standard demand).

Early-warning skill

The early warning beat climatology clearly only for September to November (Table 7). Results are for 39,716 facilities (7.07 million facility-seasons), averaged over the five held-out year blocks. Skill varied a lot between blocks: the SON AUC ranged from 0.62 to 0.94. Removing the El Niño and Indian Ocean Dipole indices did not reduce skill (SON AUC 0.77 without them, 0.71 to 0.93 across blocks), so the warning comes from the water already in the tank and the rain of the previous months, not from the climate indices.

Table 7. Early-warning skill by season (leave-years-out cross-validation, Ridge regression unless stated). Values are means over five held-out year blocks, with the range in brackets.

Season	Mean failure share	Skill vs climatology	AUC with indices	AUC without indices	AUC (XGBoost, with indices)
SON (Sep to Nov)	0.056	0.088	0.77 (0.62 to 0.94)	0.77 (0.71 to 0.93)	0.72
JJA (Jun to Aug)	0.253	0.016	0.62 (0.51 to 0.68)	0.63 (0.58 to 0.66)	0.63
MAM (Mar to May)	0.093	0.029	0.61 (0.37 to 0.83)	0.65 (0.37 to 0.82)	0.52
DJF (Dec to Feb)	0.357	0.028	0.58 (0.41 to 0.78)	0.60 (0.44 to 0.75)	0.54

Discussion

Storage, more than roof, limits most schools in the base case. Under the base assumptions, three in four schools have enough roof to meet a day-school demand on 90% of days, but the median school needs a 39.5 m³ tank, and with a 10 m³ tank the median school is supplied on only 56% of days. We do not have national data on the tanks actually installed, so we cannot say how far current storage falls short. The sensitivity analysis also shows the limits of this conclusion. If only buildings near the main school point have gutters connected, or if a school is large, the roof itself becomes the limit at more than half of schools. The national shares should therefore be read against a scenario range, from 42% to 93% of schools across the enrolment scenarios, and as low as 38% if only 30% of the mapped roof is guttered to the tank; this is not a statistical uncertainty interval. All facility-level results are screening estimates: planners should check them against their own enrolment and roof data and confirm them on site before buying tanks. Boarding schools need four times more water per pupil, and only 16.0% could meet that from their roofs, so most boarding schools need a second source.

Seasonality matters more than annual rain. The North gets enough rain in a year, but in one long season. Rules that size tanks from annual rainfall or a fixed dry period cannot capture this, which is why the dry-period rule was within 25% of the simulated tank at only 8% of facilities. It reached the target at most facilities only by over-sizing tanks. The machine-learning model reproduces the 45-year daily simulation within 25% at 97% of facilities. With a 20% safety margin, its tanks met the target at 97.5% of facilities and used 12% less storage in total than the rule, which suggests that better sizing could serve the same facilities with less storage. This holds where similar facilities are in the training data; at least 110 km from training data, only 74.5% of its tanks met the target, against 89.7% for the rule. We did not have cost data to turn this into money. The model can be used for new facilities, other demands between 100 and 20,000 litres per day, or other roof areas without rerunning the simulation, but only where similar climates are in its training data.

The climate signal is modest. Reliability has edged up since 1981, with a significant rise at about one facility in seven, mostly in the East and Centre. Tank sizes based on the full 45-year record are therefore reasonable for planning, and slightly cautious

where reliability has risen. The seasonal warning worked only for September to November, the short rains, and should not be relied on for the rest of the year. Contrary to what we expected, El Niño and the Indian Ocean Dipole added no skill on top of tank storage and recent rain at the start of the season. A simple rule of thumb follows: a tank that is low at the start of a dry season is more likely to fail, and districts could watch tank levels and recent rain when planning water trucking or rationing. This retrospective analysis supports further work on seasonal warnings, but it does not yet show how well a live warning system would perform.

Comparison with earlier work. Our finding that tank size, not roof area, limits many systems in bimodal areas, and that single-season areas need much larger tanks, agrees with single-site studies in Uganda and Ethiopia [8–10]. The national scale, the use of every facility's mapped roof, and the machine-learning sizing tool are what this study adds.

Limitations. Facility locations come from OpenStreetMap and government lists and are incomplete, especially for private schools, and some points may be offset from the real buildings. The footprints show buildings, not which ones belong to a facility or have gutters connected to a tank, and the agreement between two footprint products at 94 sites does not test this; a manual check of a sample of facilities against high-resolution imagery would strengthen the roof estimates, and facility-level recommendations should be confirmed on site. In dense towns the 60 m circle also catches neighbouring buildings, which is why the median health-facility roof in the Central region (2,407 m²) is much larger than elsewhere (about 600 m²), so Central region health results should be read as an upper bound; filtering buildings by urban density or by building type would sharpen these estimates in future work. Demand uses assumed enrolment and standard per-person needs, not measured use. CHIRPS is less accurate day by day than at monthly scales, so dry-spell lengths carry some error, the rainfall sensitivity tested only rain amount, and gauge records for validation were sparse; a fuller check with Uganda National Meteorological Authority data is needed. The model ignores leaks and other water sources. It also assumes working systems: $C = 0.8$ holds only for clean, intact gutters and a working first-flush device, and blocked or broken gutters, rusted or damaged roofs and leaking tanks lower the effective runoff in practice. The lower runoff ($C = 0.7$) and partial-connection scenarios in Table 5 show the direction and rough size of this effect, so regular maintenance matters as much as the tank size. The machine-learning sizing model reproduces our simulation, not field measurements, so it carries the same assumptions.

Conclusions

This study gives, to our knowledge, the first facility-level screening estimate of rooftop rainwater supply, tank size and seasonal failure risk for every mapped school and health facility in Uganda. Under typical assumptions most facilities have enough roof for their demand but need much larger tanks than a standard 10 m³, the single-season North needs the largest tanks, and the result for schools depends strongly on enrolment and on how much roof is connected. A machine-learning model can size

tanks almost as well as a 45-year daily simulation from a few simple inputs. Where similar facilities are in its training data, a 20% margin meets the design target with less storage than the usual rule of thumb; far from its training data, it should be used with a larger margin or checked against the simulation. Because CHIRPS rain totals were lower than gauge totals, actual supply may be somewhat higher than estimated; correcting for this mainly raises the share of facilities that can reach the target (from 77.1% to 83.1% of schools) and barely changes the tank each one needs, because tank size is set by the length of the dry season rather than by the rain total. The estimates need confirmation on site, especially which roofs are connected to a tank, but the open results and models can help ministries, districts and partners decide where tank investment is most needed.

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Competing interests

The authors have declared that no competing interests exist.

Author contributions

Conceptualization: Okello Benjamin, Oler Patrick.

Methodology: Okello Benjamin, Oler Patrick (health facility water demand).

Data curation, formal analysis, investigation, software, validation, visualization, writing (original draft) and writing (review and editing): Okello Benjamin.

Data availability

All code (Python and Google Earth Engine JavaScript, MIT licence), the cross-validation fold assignments, and the facility-level results for all 41,592 facilities (CC BY 4.0) are available on Zenodo at <https://doi.org/10.5281/zenodo.23431663>, in two parts: the code and results, and the input rainfall and boundary files needed to rerun the analysis. Input data are public: Open Buildings v3 and CHIRPS through Google Earth Engine, health facility lists from Maina et al. [14] and the Ministry of Health, and schools from OpenStreetMap (ODbL).

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Supporting information

S1 File. Facility-level results for all 41,592 facilities (CSV).

S2 File. Sensitivity analysis results by scenario and facility group (CSV).

S3 File. Machine-learning tank-sizing skill, unlimited-storage feasibility check, buffered margin test, fold assignments, cross-validated predictions and SHAP importance (JSON and CSV).

S4 File. Early-warning skill by held-out year block, with and without climate indices (CSV).