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Electronic sensors to monitor functionality and usage trends of rural water infrastructure in Plateau State, Nigeria

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ABSTRACT

Internet-connected sensor technologies have recently been used to monitor water service infrastructure in remote settings. In this study, 397 groundwater pumps were observed in Plateau State, Nigeria over 12 months in 2021. Two hundred of these sites were instrumented with remotely reporting electronic sensors, including 100 hand-pump sensors, 50 electrical pump sensors, and 50 cistern water-level sensors. Every two months, phone calls and site visits were used to collect a ground-truth of pump functionality: whether the pump was capable of delivering water, regardless of actual use. Our study examined: (1) What are the operating characteristics and trends of these different kinds of water pumps?; (2) Can water-point functionality be predicted with electronic sensors?; and (3) Does the instrumented water-point sample accurately represent average water-system functionality across the region? An automated classifier generated functional/non-functional diagnostics for instrumented pumps on a weekly basis. Classifier diagnostics were compared to ground-truth data, showing an overall accuracy of 91.7% (96.1% for hand-pumps, 63.9% for cisterns, and 93.2% for electrical boreholes), with high fleet-wide sensitivity in correctly identifying a functional pump (94.4%), but poor overall specificity in correctly identifying a non-functional, broken pump (25.0%). This discrepancy is attributable to the sensors' difficulty in distinguishing between a broken pump and an unused pump. Varied patterns were seen in pump usage as a function of rainfall, with hand-pump use decreasing significantly, electrical pump usage decreasing to a lesser degree, and cistern use increasing in response to local rainfall. A comparison of the 200 instrumented to 197 non-instrumented sites showed statistically similar repair and failure rates. The high overall accuracy of the sensor–diagnostic system—and the demonstration that sensor-instrumented sample sites can represent population-level breakdown and repair frequencies—suggests this technology's utility in supporting sample-based monitoring of overall water pump functionality and water volume delivery. However, the poor performance of the system in distinguishing between broken and unused pumps will limit its ability to trigger repair activities at individual pumps.

1. Introduction

1.1. Background

Nigeria faces increasing desertification associated with drought in recent years, including in Plateau State (Olagunju, 2015), reducing surface water resources and increasing reliance on groundwater for domestic, livestock, and agricultural uses (*Gongden and Lohdip, 2009). Across sub-Saharan Africa, groundwater resources and recharge are

considerable, marking a significant source of future water security for the continent and an important consideration for resilience in the face of climate change (MacDonald et al., 2021; Taylor et al., 2009).

Rural water-supply interventions aim to improve water security in low-income settings. However, they often have a less-than-expected record of sustaining water services. Examples abound of technologies whose useful lives were cut short by preventable causes such as lack of operation and maintenance budgets, expertise, or supply chains

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for replacement parts, and conflicting management priorities (Boudet et al., 2011). This is illustrated by the failure rates of hand-pumps in rural communities in Africa, where as many as one in three are non-functioning at a given time (Foster et al., 2020; Klug et al., 2018). Other technologies fail to scale because supporting systems—including economic and political contexts—are insufficient (Brown et al., 2009; Hollander et al., 2020), or because technical or social components of the interventions were poorly designed at the outset and proved unacceptable to end-users (Luoto et al., 2011).

As described in recent literature (Thomas et al., 2018; Andres et al., 2018; Thomas and Brown, 2021), new approaches and technologies to monitoring how well interventions sustain or improve service delivery for the world's poorest and most vulnerable offer compelling opportunities to make rural water supply more secure and reliable. In recent years, electronic sensors were developed and applied in environmental health programs to support health studies and provisioning of water services. This study supports research into the potential for technology solutions to support service delivery in the rural water sector in Low- and Middle-Income Countries (LMICs). Specifically, the objective was to analyze the potential for remote/wireless technologies to monitor and predict the functionality of rural water infrastructure in developing economies, with a study in Nigeria.

1.2. Objective

Previous literature has examined the use of near-real-time reporting sensors as direct water-point operations and maintenance (O&M) support tools in Rwanda and Kenya (Nagel et al., 2015; Wilson et al., 2017); quantified groundwater use changes as a function of local rainfall in Kenya (Thomas et al., 2019; Thomson et al., 2019); analyzed site functionality across motorized boreholes in Northern Kenya (Turman-Bryant et al., 2019); and called for the application of better and more responsive monitoring systems to create accountability feedback mechanisms between service providers, funders, and communities (Thomas and Brown, 2021). Additional has research leveraged networks of sensor-equipped boreholes to support improved service-delivery models (Libey et al., 2022).

An O&M monitoring approach prioritizes mechanisms to monitor all water systems that a water supplier (e.g., a utility, NGO, or government agency) is responsible for operating and maintaining. While an O&M monitoring approach may not require Internet-of-Things (IOT) connected sensors on all water-points, it does require consideration of the viability and capacity of water system management organizations to use and respond to the generated data. Operations and maintenance monitoring is sensitive to equipment cost as it can require a considerable proportion of water schemes to be instrumented. In contrast, the objective of this study is to retroactively examine the operating characteristics of a sample of electrical and manual boreholes in Plateau State, Nigeria, to support an estimation of water system functionality. These data can help to inform investments, policy, and progress, but were not intended to support real-time operations.

Following the sensor deployment phase of the project, sensor data analysis was performed to answer the following research questions:

- What are the water-pump operating characteristics and trends?
- Can water-point functionality be predicted?
- Does this statistical sample accurately represent water system functionality in Plateau State?

2. Methods

The study deployed satellite-connected sensors provided by Virridy (previously SweetSense, Inc.) on hand-pumps and electrical pumps in Plateau State, Nigeria. Sensors collected data on pump run time and functionality, used to analyze trends in water-pump use and functionality predictive power.

2.1. Study setting

Plateau State is located in central Nigeria, West Africa. It is one of the 36 states that, along with the Federal Capital Territory of Abuja, constitute the Nigerian Federation. Plateau State has an estimated population of 4.2 million (NBS, 2006), of which only an estimated 44.9% have access to basic water services (Federal Ministry of Water Resources and National Bureau of Statistics, 2018). Plateau State comprises 17 Local Government Areas (LGAs). A map of the study area is shown in Fig. 1.

2.1.1. Statistical approach

An expert-informed predictive model was developed, and its ability to determine water-pump functionality and failures was analyzed against ground-truth observations. Using contact data collected during on-site asset inventory, ground-truth data was collected via phone calls every two months to ascertain the functionality of the pump and reasons for any non-functionality. When a phone call could not be completed successfully, a site visit was carried out.

The characteristics of the sites selected for inclusion in this study might vary from the characteristics of similar sites in Plateau State. Therefore it was important to compare water system functionality trends and estimates generated with sensor data against other data sources collected in the study area. Because the statistical sample reflects initially-functional water points only, it is biased toward water-scheme functionality.

2.1.2. Water scheme database development

To select a robust sample of water points to instrument, an indicative database of water points in Plateau State was developed. This was generated by reviewing data provided by the World Bank, the Plateau Rural Water Supply and Sanitation Agency (PRUWASSA), the Community and Social Development Project (CSDP), and Water Aid Nigeria (WAN). Next, the team merged these databases, de-duplicated records, corrected obvious typographic errors, and unified categorical variables. Detailed ground-truthing and additional error correction were conducted on a sub-sample of candidate sensor installations. Several data sources were consulted that provided qualitative and quantitative characteristics on national and regional administrative levels in Nigeria, as well as several databases with site-level water system data.

Databases which contributed to this unified water scheme list include Nigeria's national Water, Sanitation, Hygiene Information Management System (WASHIMS); informant interviews conducted in Plateau State in February 2020; two World Bank reports (Bank, 2017; Andres et al., 2019); a CSDP inventory of water systems; a PRUWASSA database of water points and schemes for Plateau State (2015); and the 2018 Water, Sanitation, Hygiene National Outcome Routine Mapping (WASH-NORM) survey (Federal Ministry of Water Resources and National Bureau of Statistics, 2018).

The most comprehensive source about water systems in Plateau State was the database of water points and schemes provided by PRUWASSA and the World Bank. This list included 3,066 water points and 32 water schemes. The CSDP inventory was then integrated with this list to develop a harmonized list of 3,113 water points, summarized in Table 1. This list suggests that 81% of known water systems in Plateau State are hand-pumps, of which 53% are functional, and 18% of water systems have electrical pumps, of which 46% are functional.

2.1.3. Sample size estimation

Based on these estimates, Table 2 presents a sample size calculation for the number of sensors required to provide a statistically valid sample of monitored water points, stratified by electrical and hand-pumps.

These estimates suggest that approximately 758,100 people are served by approximately 2,500 hand-pumps, and approximately 1.38M people are served by 552 electrical pump systems, for a total served

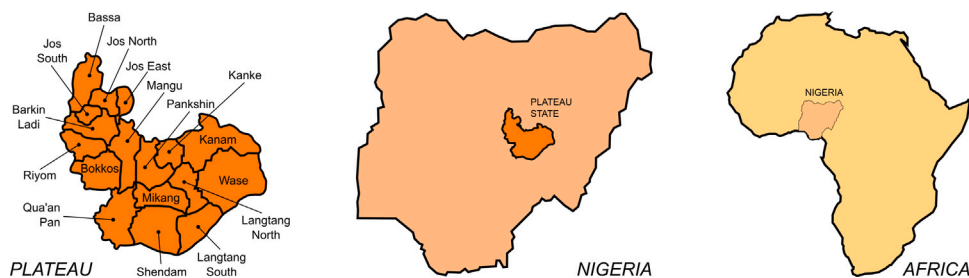


Fig. 1. 17 Local Government Areas (left) are situated within Plateau State (center), in central Nigeria (right).

Table 1
Harmonized Plateau State water systems summary.

	Handpumps		Electrical pumps		Other		Total	
	Count	Proportion	Count	Proportion	Count	Proportion	Count	Proportion
Functional	1,334	53%	252	46%	19	56%	1,605	52%
Non-functional	1,193	47%	300	54%	15	44%	1508	48%

Table 2
Sample size estimation calculation features.

Estimated number of handpumps (See Table 1)	2,527
Estimated population served per handpump (RWSN, 2022)	300
Total estimated population served by handpumps	758,100
Estimated number of electrical pumps (See Table 1)	552
Estimated population served per electrical pump (MacAllister et al., 2020)	2,500
Total estimated population served by electrical pumps	1,380,000
Total estimated population Plateau State (NBS, 2006)	4,200,000
Plateau state access to basic water services (Federal Ministry of Water Resources and National Bureau of Statistics, 2018)	44.9%
Population with access to basic water services	1,885,800
Confidence level, Interval	95%, 10%
Number of functional handpumps (See Table 1)	1,334
Handpump sample size	90
Number of functional electrical boreholes (See Table 1)	252
Electrical borehole sample size	70
Total sensors required	160

population of about 2.14M. To validate these estimates, a top-down estimate of the population in Plateau State was multiplied by the latest WASH NORM survey (Federal Ministry of Water Resources and National Bureau of Statistics, 2018) findings on access to basic water services in the state (44.9%), yielding about 1.9M million people with access to basic water services.

Based on these calculations, we produced, delivered and installed up to 200 sensors comprising a mix of hand-pump and electrical borehole sensors to provide a robust, statistically significant estimate of water system functionality across the state.

2.1.4. Sample selection and site validation

The harmonized water points list provided a short-list of candidate water systems. The World Bank Water Global Practice was responsible for the random selection, using exclusion criteria based on safety and other considerations deemed relevant by PRUWASSA (e.g., known water-system functionality, promoter, and water-system type). The following criteria were applied prior to randomization: (1) only motorized pumps and hand-pumps, and (2) only pumps identified as or assumed to be functional.

The World Bank Water Global Practice then applied the following criteria to sample generation: (1) stratified by CDSP and PRUWASSA managed water systems; (2) 30 randomly selected CDSP sites (all hand-pumps); (3) 100 randomly selected motorized boreholes and 70 hand-pumps stratified by project implementer; (4) 19 randomly selected observations as first backups; and (5) 22 additional randomly selected observations as secondary backups. Note that backups were distributed proportionally accordingly to the criteria above to the extent possible.

Initially, the project team intended to validate the selected sample sites through phone calls to confirm pump presence, type, functionality, and physical safety and security prior to a site visit. However, limited data on the water points resulted in ambiguities when attempting to contact local operators and communities. Instead, the team conducted site visits, which included a combination of community engagement, site validation, asset-inventory surveys, and sensor installations if appropriate. During site visits, an asset inventory survey was deployed through the mWater app, and included questions on water site location, pump caretaker contact information, infrastructure characteristics, installation year, management structure, functionality, number of users, water-use behaviors (including seasonal influence), alternative water sources, tariffs, water volume yields, and recent maintenance. Additionally, the survey process included taking pictures of the pump and any visible components.

2.2. Sensor operation

Virridy sensor systems comprise a satellite-connected Gateway that logs and transmits data at a 12- or 24-hour frequency, and an Accessory that collects data to transmit to the Gateway at a 40-minute frequency, which minimizes daily satellite data-transmission costs. The Gateway is powered by a solar panel, while the Accessory is self-powered.

Three types of sensor systems were used to instrument water-pump infrastructure in Plateau State: (1) AC-powered electrical boreholes were instrumented with self-powered inductive current clamps; (2) DC-powered electrical borehole cisterns were instrumented with battery-powered water-level sensors; and (3) India Mark 3, India Mark 2, and AFRIDEV hand-pumps were instrumented with battery-powered direct-use sensors (see Fig. 5). Both the AC electrical and hand-pump sensors

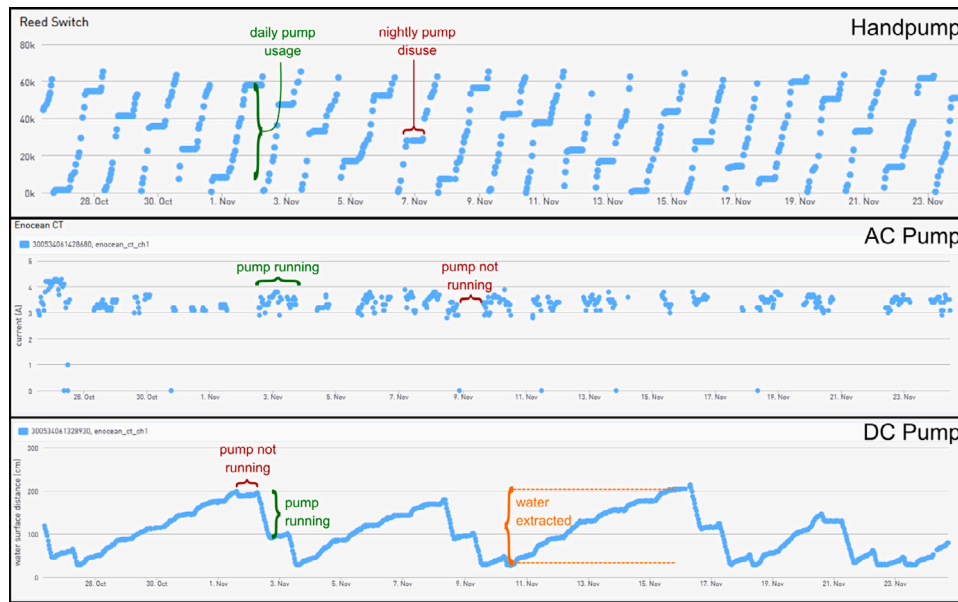


Fig. 2. Three sensor types were used to measure usage at three types of pumps. Hand-pump sensors convert handle motion counts into usage estimates (top). AC current clamps use 40-minute current readings to estimate runtime (center). Water level sensors in storage reservoirs convert water level changes to filling and emptying events on DC pumps (bottom).

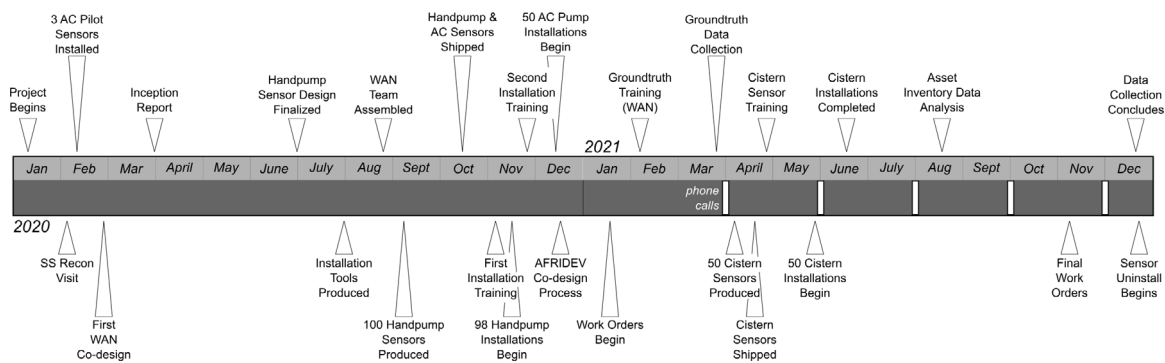


Fig. 3. Project milestones relate to this study spanned 2020–21.

record direct measures of pump use. The cistern sensor measures water supply in storage tanks on-site as a proxy for water-system use. Fig. 2 shows the operating principles behind converting raw data from each sensor type into estimates of pump run time and water extraction.

2.3. Implementation process

A broad timeline describing the scope and activities in this project is shown in Fig. 3.

Amid travel restrictions related to the COVID-19 pandemic, the team organized virtual training sessions with in-country partners, WAN and PRUWASSA. Training comprised sessions for each sensor installation type. Following each training, partner feedback was incorporated into training materials. Additional feedback from partners enabled a co-design process to improve sensor deployment opportunities. Persistent 3D models were made available to installers to internalize the mechanics of the sensor system and support in-field installation processes.

Detailed installation manuals were provided by the sensor designers. Each installation manual was modified in response to stakeholder input following initial review, and following training sessions and evolving field knowledge. Manuals went through several iterations, incorporating feedback from in-country design collaborators. The final manuals are shown in Fig. 4.

Partner teams used the mWater platform to record data about potential installation and control sites in an asset inventory form. Additionally, at each installation site, and each time a sensor was installed, removed, or replaced, a smartphone-based survey (mWater) was completed by the technician performing the work. This form records the installation location, barcode of the gateway, type of accessory installed, and collects other relevant asset and site data, including installation pictures.

A number of mechanical, electrical, and site issues required continual operations and maintenance activities to be carried out in partnership with WAN and PRUWASSA staff to maintain sensor functionality and record events such as complete pump-site failure, sensor system theft or vandalization, etc. Staff continually monitored the raw data coming from each sensor site, and deployed mWater-based Work Orders on roughly a monthly basis for site visits to respond to apparent sensor system or site issues.

2.3.1. Sensor system deployment

Water facilities that met the following criteria were prioritized for sensor installation: (1) Located in rural or small-town area; (2) A public good with unrestricted access by the public; (3) Located in an operationally safe Ward and LGA; and (4) Sensor instrumentation is acceptable to the community, identified through the initial asset inventory interview with the pump operator or caretaker.



Fig. 4. Three installation manuals were developed with support and iterative input from project stakeholders.

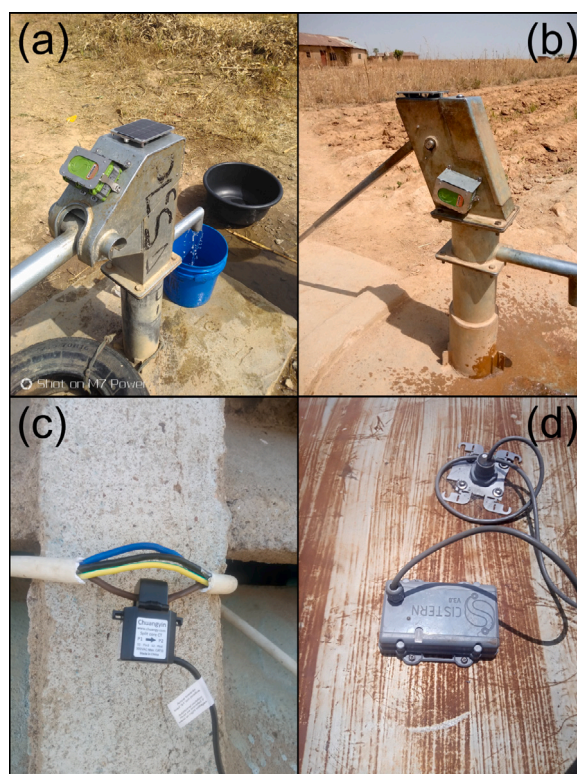


Fig. 5. Sensor installations on rural water Afridev handpump (a), India MkIII handpump (b), AC electrical motorized pumps (c), and DC borehole on-site steel cistern (d).

2.3.2. Asset inventory, ground-truth, and classifier training set

In collaboration with local government leaders, pump reports of water system status (functional or non-functional) were collected using mWater. For both sensor-equipped pumps and a comparison sample of non-sensor-equipped pumps, complete asset-inventory surveys were first collected through in-person visits. Then, the operators of these pumps in both samples were called every two months starting in April 2021 to record pump functionality status. Sometimes the operator could not be reached by phone, in which case the team physically visited the site to confirm the operational status of the pump in question. In addition to these scheduled visits and phone calls, pump status reports were submitted during sensor-data-triggered field visits and

phone calls, reviewed by program staff for data completeness and for accuracy of repair and failure event dates.

In combination, these reports provided details on the ground-truth status of both the pumps and the sensors. Event dates from the reports enabled comparison with sensor data, and where pump report dates were found to be misaligned with pumping data, data validation was performed based on field team recall, other available status reports, and sensor run-time data. When known, repair events were logged and incorporated into this analysis as known periods of non-functionality before the repair, and known functionality after the repair.

WAN and PRUWASSA team members carried out asset inventory baselining in March and April 2021. All asset inventories included a

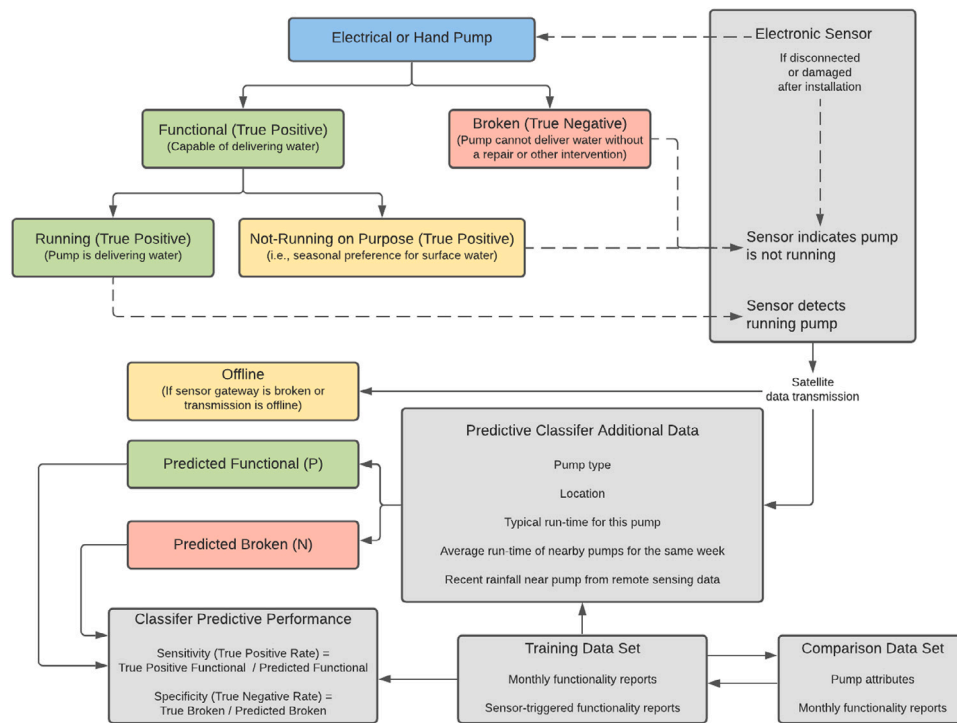


Fig. 6. A conceptual model describing the operating conditions of the groundwater pump system, sensor and remote sensing data sources, interpretation approach, and classification conditions.

site visit, interviews with local caretakers, and an inventory of the population served by the pump, and other demographic data. At each site, at least one caretaker's contact information was recorded, with a secondary caretaker's contact information included when possible. WAN and PRUWASSA then made ground-truth phone calls and site visits every two months.

2.4. Pump functionality prediction algorithm development and validation

The algorithms described in this report were developed by leveraging a combination of in-situ and remotely sensed data validated with manually collected ground-truth. We built on related efforts with similar systems in Kenya and Ethiopia (Thomas et al., 2020; Thomas and Brown, 2021). The flowchart shown in Fig. 6 describes the operating conditions of the groundwater pump system. Each pump has two primary, real-world conditions: it is either "Functional" and capable of delivering water, or it is "Non-functional" and cannot currently deliver water. A non-functional pump includes pumps that require a repair or management intervention, and sites where local drought conditions prevent water extraction. The classifier was calibrated and evaluated through comparison against the ground-truth site reports and periodic phone calls to confirm water-pump functionality.

As a first-order approximation to distinguish functional from non-functional conditions, electrical run-time sensors indicate if the pump is switched on or off, cistern sensors detect changes in water level, and hand-pump sensors detect handle motion. However, these approximations are insufficient to reflect the operating environment for these pumps. Namely, many pumps may not be used during the rainy seasons in these regions even if they are functional, when people are otherwise able to secure surface water for themselves and their livestock. A more sophisticated classification system is required to distinguish between "Non-functional", a true-negative condition, and "Not-running on purpose", a true-positive condition where the pump is capable of delivering water, even if it is not being used. The following sections describe the data-collection and interpretation methods applied to improve on this distinction.

Our work previously used remotely sensed rainfall estimates from the Monthly Climate Hazards Group InfraRed Precipitation with Stations (CHIRPS) (Funk et al., 2015) data to show that pump usage inversely correlates to local rainfall, and that groundwater demand increases when absence of rainfall limits the availability of surface water alternatives (Thomas and Brown, 2021). Therefore, in the predictive classifier described in this report, remotely-sensed data for rainfall estimates were incorporated using the CHIRPS system in order to use rainfall as a potential predictor of pump run-time. Each data point corresponds to a 0.05° area, or roughly 31 square kilometers.

2.5. Water pump run-time analysis

In this analysis, time-series methods are used to evaluate trends in water system functionality collected from the instrumented water pumps. The key outcome is pump functional time, operationalized as the count of functional pump hours, and collected on a continuous basis during the study period via installed sensors. Data on functional time is aggregated into weekly time intervals, and is generally presented as a percentage of total run-time, compared to a maximum run-time of 100%, which would indicate 24-hour daily usage.

2.6. Expert classifier design

To build and then validate our classification algorithm's ability to detect pump functionality, a training set was used that reflects a ground-truth of pump conditions. To associate the site-report ground-truth data with the daily sensor readings, the site-report data needed to be extended to adjacent days when the apparent state was unchanged. To accomplish this, the sensor data was segmented into "blocks" of use or non-use. Pump days were categorized as either usage (at least two sensor readings of activity) or non-usage (zero or one sensor readings of activity). Contiguous runs of days of usage or non-usage were treated as a block of unchanging state. Blocks were smoothed by eliminating short blocks of non-usage (shorter than seven days). Finally, contiguous blocks were truncated at plus or minus 30 days from the ground-truth

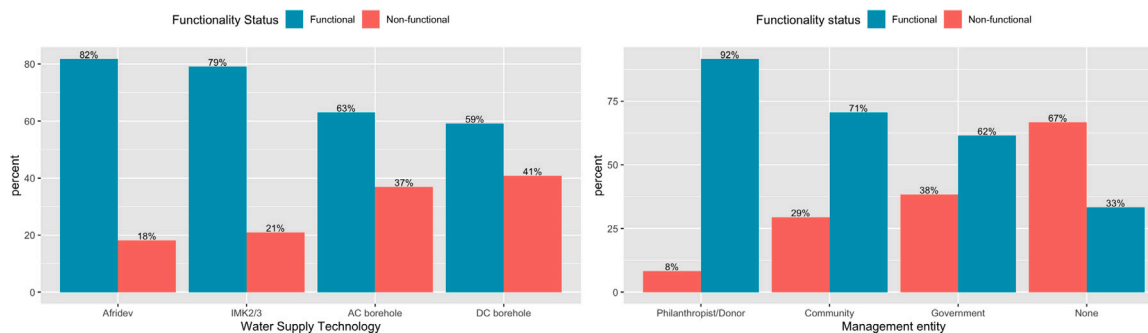


Fig. 7. Baseline functionality rates across water supply technology types (left) and across management types (right).

site report and a new block started in order to minimize the risk of separate pump states and site reports being grouped together. Thirty days was chosen as an approximation of the Nyquist rate for sampling at twice the frequency of the signal measured (Candes and Wakin, 2008). The algorithm truncates at 30 days plus or minus the report date to minimize the chance that a block captures both rainy and dry seasons. In other words, any wider of an estimating window could transect seasonal changes in rainfall and therefore pump demand. Any site report dated within a block was then assumed to reflect the true status of the pump for the entirety of the block.

3. Results

3.1. Asset inventory baseline findings

3.1.1. Water supply technology distribution, management and baseline functionality

A total of 400 water points were initially selected for inclusion in the study (200 sensor instrumentation sites and 200 comparison control sites). These 400 study sites comprised four types of water supply technology: two types of hand-pumps (Afridev and IMK2/3), and two types of electric boreholes (AC-powered boreholes and DC-powered boreholes). Overall, hand-pumps were the most prevalent technology among the study sites (52%). Afridev hand-pumps made up 30% of the study sites, India MK2/3 hand-pumps made up 22%, and AC and DC electrical boreholes made up 25% and 23% respectively. Following site visits, 3 control sites had insufficient data to track them, decreasing the overall sample to 397 sites.

A vast majority (90%) of study facilities were under the management of the communities they served. Other management entities were Philanthropist or Donor (6%) and the Government (3.2%). Some facilities (0.8%) lacked any form of management. Including both instrumented and control sites, overall baseline functionality among all study facilities was 71%, with a 59%–82% range across all water supply technology types. Afridev hand-pumps had the highest functionality rate, while DC-powered boreholes had the lowest (see Fig. 7).

Functionality rates were highest among facilities managed by philanthropists or donors, and lowest among facilities without a management entity or those managed by the government. Note that April data are not included in these figures because site selection continued through May, causing an overlap between baseline and observed data until June.

3.1.2. Geographical location

Study sites were located across all 17 LGAs of Plateau State. Some LGAs had a higher share of instrumented sites than others. For example, Kanke LGA had the highest share, at 11%, while Langtang South had the lowest, at 1%. The vast majority (91%) of study sites were located in rural or small-town settings. The remaining 9% were located in urban settings.

3.1.3. Attributes of baseline functionality status

The results of a logistic regression model on water facility attributes show that some are important in relation to the functionality status of the facility. These include: (1) the management status; (2) the type of pump; and (3) the payment method for the water service. Facilities with inactive or unknown management status were less likely to be functional at baseline ($p < 0.001$ and $p = 0.013$, respectively). Similarly, facilities with hand-pumps were more likely to be functional compared to facilities with electric pumps ($p < 0.001$ for Afridevs, $p = 0.029$ for IMK2/3). Additionally, facilities where users did not pay for the water service were less likely to be functional ($p = 0.038$). On the other hand, the setting, either rural or urban, was not found to be a statistically significant predictor of baseline functionality ($p = 0.601$, $p = 0.623$).

3.1.4. Comparison of sensor and non-sensor study sites

Significant differences exist between sites selected for sensor selection ($n = 200$) and the comparison sites ($n = 197$), as shown in Table 3. While Pump and Management Types were not significantly different for the two study groups, Management Status, Water Quality Testing Status, and Last Known Functionality Status all differed significantly. Additionally, baseline functionality was significantly different between the sensor and non-sensor study sites. This is a result of the selection criteria for study sites, which required that a pump be functional for a sensor to be installed there. This functionality requirement was not applied to the comparison group, which was otherwise selected with the same random sample approach.

3.2. Observed functionality over time, and failure and repair rates

Functionality over time was determined by repeat phone calls. Baseline functionality is based on asset inventory surveys, and functionality change points between phone calls were tracked and are presented in this section. These failures and repairs serve as ground-truth data for comparison with sensor-based classifiers.

3.2.1. Pump functionality levels over time

Fig. 8 shows reported functionality of pumps by study group and by pump type. There are significant differences between the sites at which sensors were installed and the non-sensor sites. Especially notable is the very low functionality of DC boreholes in the control group.

Overall, 43% of the control sites were functional on average, with a standard deviation of 2.2%. In contrast, 88% of the sensor sites were functional on average, with a standard deviation of 6.0%.

3.2.2. Breakdown and repair events over time

While the overall functionality of the two groups differs, the rates of failure and repair are similar. A relatively flat level of functionality in both groups is maintained by close parity between breakdown and repair events. Several sites lacked sufficient data to conduct this analysis, reducing the number of analyzed sites to 390 (195 sensor sites, 195

Table 3
Comparison of sensor and non-sensor sites.

	No Sensor (N=197)	Sensor (N=200)	P-value
Pump Type			
Borehole	87 (44.2%)	103 (51.5%)	0.173
Handpump	110 (55.8%)	97 (48.5%)	
Management Type			
Community	83 (42.1%)	160 (80.0%)	0.372
CSDP	1 (0.5%)	0 (0%)	
Government	1 (0.5%)	3 (1.5%)	
None	3 (1.5%)	2 (1.0%)	
Philanthropist	8 (4.1%)	19 (9.5%)	
Donors	0 (0%)	3 (1.5%)	
Missing	101 (51.3%)	13 (6.5%)	
Management Status			
Active	121 (61.4%)	186 (93.0%)	<0.001
Don't know	7 (3.6%)	1 (0.5%)	
Not active	69 (35.0%)	13 (6.5%)	
Water Quality Testing			
Don't know	115 (58.4%)	77 (38.5%)	<0.001
No	79 (40.1%)	95 (47.5%)	
Yes	3 (1.5%)	28 (14.0%)	
Last Known Status			
broken	110 (55.8%)	34 (17.0%)	<0.001
functional	87 (44.2%)	163 (81.5%)	
Missing	0 (0%)	3 (1.5%)	

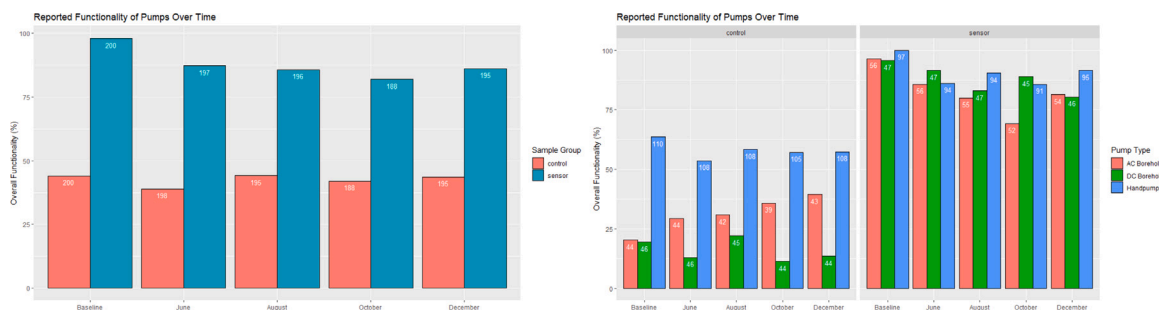


Fig. 8. Functionality levels of sensor and non-sensor sites differed considerably. The functionality of sensor-equipped sites was much higher than control sites (left). Within sample groups, there were considerable differences in the makeup of functional pumps (right).

Table 4
Breakdown and repair events observed via bimonthly calls.

	April	June	August	October	December	SUM
Control breakdowns	10	12	10	15	7	54
Control repairs	13	10	18	8	14	63
Instrumented breakdowns	19	18	13	16	9	75
Instrumented repairs	3	13	9	10	16	51

control sites). For the majority of pumps, no breakdown was observed during the study period (147 sensor sites, 140 control sites). A significant number of pumps saw one breakdown (45 sensor, 48 control), with a smaller number of sites seeing two breakdowns (3 sensor, 6 control), and one site in the control group seeing three breakdowns. Table 4 shows the record of repairs and breakdowns by study group. One-way ANOVA tests showed no statistically significant differences between sensor and non-sensor sites for pump failures ($F(1,6) = 1.35$, $p = 0.289$) or pump repairs ($F(1,6) = 0.034$, $p = 0.86$).

3.3. Sensor site asset inventory results

Much of the analysis that follows focuses on sensor sites, with usage data generated by transforming raw sensor feeds into hourly or weekly usage totals. Due to significant differences shown between sensor and non-sensor sites, it could be useful to examine sensor-specific site properties: pump types at sensor-enabled sites were AC Electrical (28%), Afridev hand-pump (26%), DC Electrical (23%), and India Mark 2/3 Handpump (22%). Of the electrical boreholes, 52% were rural, 29% were small-town, and 18% were urban settings. For hand-pumps,

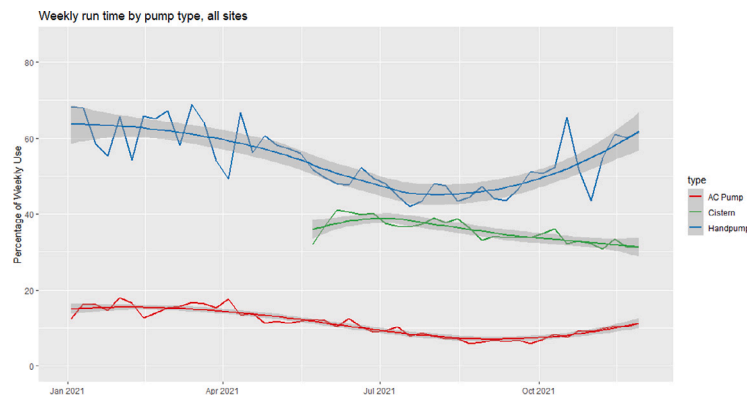


Fig. 9. Average run-times as percentages of possible daily usage, displayed by pump type.

these respective settings were 90%, 9%, and 1%. Installation quantities varied by LGA, with the most sensors installed in Bassa and Mangu (13% and 10%) and the fewest installed in Qua'an Pan, Kanam, and Jos East (each 2%).

3.4. Pump usage results

Raw data from three types of sensors were converted into an approximate daily run-time at each site. These processed data take the form of percentages of daily run-time; that is, 100% would imply that a pump was running 24 h per day, 50% would imply 12 h per day, and so on.

Overall estimated run-time of each pump type is shown in Fig. 9. These data are displayed as weekly averages with a smoothed usage line overlaid.

Hand-pump daily usage (average 13.5 h per day) is much higher than AC pump usage (average 2.6 h per day), and both decrease during the rainy season. DC pump average usage falls between the other types (8.4 h per day), and appears to respond to the rainy season in the opposite direction. While the cistern sensors installed to track usage on DC pumps were installed roughly half-way through the project because of programmatic logistical delays, this data was incorporated into our analysis in aggregate. There is no anticipated impact on the statistical reporting as metrics are presented in aggregate and control for seasonal impacts. The data included here are weekly averages across three date ranges: 11/29/2020 to 12/26/2021 for hand-pump sensors, 12/13/2020 to 12/26/2021 for AC electrical sensors, and 5/23/2021 to 12/26/2021 for DC water level sensors.

3.5. Expert classifier and sensor system results over time

The Expert Classifier algorithm described in the Methodology section assigns a Status to each pump for each week of run-time, drawing on the pump's prior usage and local rainfall data, allowing the algorithm to identify periods of Normal and Low use, or Seasonal Disuse. One way to examine these data is in terms of incidence over time. Fig. 10 shows weekly incidence of each status type. Note that the category "Seasonal" (meaning Seasonal Disuse) often replaces incidents of the category "No Use" during the rainy season, indicating that the classifier algorithm is likely over-estimating the impact of seasonality on pump functionality.

One important factor influencing the adoption of IOT technology for remote monitoring is the reliability of sensor technology. Sensors require maintenance, which can increase the total O&M workload for pump maintenance. Over the course of the year-long deployment of sensors in this study, overall sensor system functionality dropped from 85% to 69%, as shown in Fig. 11. "Offline" refers to a satellite gateway that is not communicating with the satellite. "No Data" refers to a

system where some other component of the sensor system has failed. "TOTAL OFFLINE" is the sum of these statuses.

Following each work-order site visit, the issue found was logged based on notes from the team in the field, with the goal of analyzing which failures were mechanical (a broken component, a disconnected solar panel, etc.) and which failures were non-mechanical (non-functional electronics, insufficient solar resource, etc.). Over the course of the project, these work order results were classified as: Reed Switch Disconnected or Broken (4%); Reed Switch or Bracket Damaged or Moved (3%); Solar Panel Disconnected or Broken (11%); Vandalized or Stolen (13%); Vibration Damage (1%); Water Damage, (3%); or Other or Unknown Mechanical Failure (6%). In total, 41% of work-order visits found some mechanical problem as the source of the sensor system issue, with theft or vandalism the most common cause, closely followed by a disconnected or severed solar panel.

3.6. Expert classifier performance

In previous research, the performance of a similar classifier algorithm showed high sensitivity (true positive rate) (82%), but relatively low specificity (true negative rate) (50%) (Thomas et al., 2021). We find similar results from this study—namely, the statuses generated by the classifier do a good job of predicting when a pump is functional, but are less skilled at discerning when a pump is not functional vs. simply unused.

Fig. 12 shows four potential outcomes of classifier performance. These plots show: (a) several true-positive conditions (blue), illustrating a highly used and functional pump, detected by the sensor and confirmed by two site reports; (b) both true-positive (blue) and true-negative (green) conditions, illustrating the sensor data and expert classifier accurately detecting a pump in its functional and broken states; (c) true-positive (blue) and false-positive (red) conditions, showing that the expert classifier interpreted sensor noise as pump functionality; and (d) true-positive (blue) and false-negative (purple) conditions, showing that the sensor was damaged or moved, and is falsely reporting the pump as non-functional.

Overall, the expert classifier model had high sensitivity but relatively low specificity. Table 5 shows the performance characteristics of the expert classifier.

3.7. Influence of rainfall on run-time

As described in previous work, seasonality can significantly impact water-pump demand and usage. Specifically, we observed decreases in groundwater usage in areas where surface water availability increases due to local rainfall, and increases in groundwater demand in response to drought (Thomas et al., 2019). We saw an overall 22.9% increase in borehole run-times following local rain deficit, a 1.1% decrease in borehole use one week after each 1 mm increase in rainfall in Kenya,

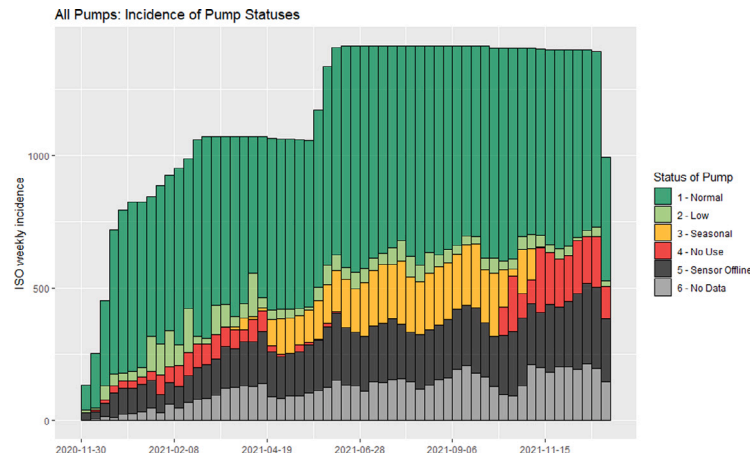


Fig. 10. Cumulative weekly incidence of sensor-based classifier statuses over time. Note a large increase in overall weekly incidence in early June, when DC pump sensors were installed on raised water cisterns.

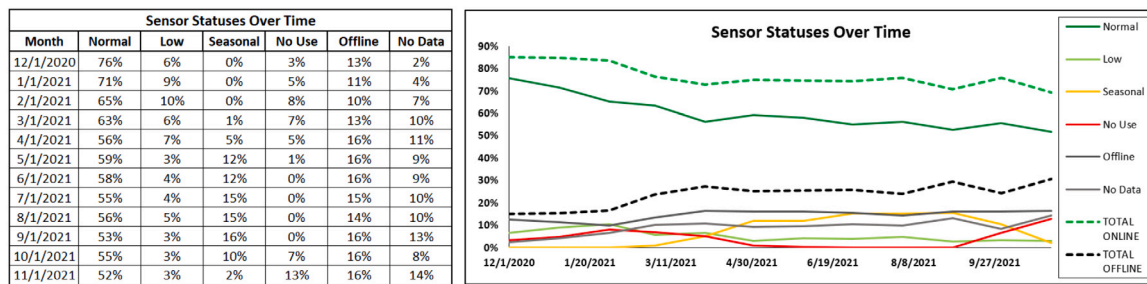


Fig. 11. Monthly aggregated sensor system statuses.

Table 5

Classifier performance, where a true positive is a functional pump and a true negative is a non-functional pump.

Performance metric	Expert classifier performance
All data (functional and non-functional pumps)	
Overall accuracy	91.7%
True positive rate (sensitivity)	94.4%
True negative rate (specificity)	25.0%
Positive predictive value	96.1%
Negative predictive value	15.0%

and a 1.3% decrease in borehole use after each 1 mm increase in Ethiopia.

This study compares run-times to average daily rainfall aggregated by week. Rainfall is estimated from remote sensing observations from CHIRPS data. As shown in Fig. 13, rainfall influences pump run-times across all data, from all instrumented pumps. On average, there is a decrease of 1.8% daily run-time per 1 mm of rainfall. This regression was run on weekly averages of daily rainfall and pump usage.

To test the sensitivity of the regression to zero-rainfall weeks, a linear fit was also applied to the data after removing all completely dry weeks. While the goodness of fit remained roughly the same ($R^2 = 0.3$ with dry weeks, $R^2 = 0.28$ with no dry weeks), the slope of the line changed significantly. To further examine the impact of zero- and low-rainfall weeks, the data was binned into dry weeks (no rainfall) and three equally-sized bins of non-dry weeks, showing an increase in the significance of rainfall on pump run-time as rainfall conditions become wetter.

This linear regression analysis was repeated on the LGA level, and the results are shown in Fig. 14. This reveals differing responses to rainfall across LGAs. Several LGAs are not included in these visualizations due to low levels of instrumentation or available data.

Finally, the relationship between run-time and rainfall was examined as a function of pump type, shown in Fig. 15. Hand-pumps are significantly more impacted by local rainfall ($R^2 = 0.54$), followed by AC boreholes ($R^2 = 0.27$). DC boreholes, where cisterns were instrumented, have a lower coefficient of determination ($R^2 = 0.25$) and respond in the opposite direction to local rainfall. Possible reasons for this are discussed below. Overall, monthly rainfall levels appear to have a strong impact on pump run-time. The impact of rainfall on pump use is especially apparent at hand-pump sites, where a 1 mm increase in local rainfall correlates to roughly a 30-minute decrease in pump run-time on average.

4. Discussion

4.1. Observed functionality patterns

Phone calls and site visits carried out every two months indicated relatively stable levels of functionality across both sensor and non-sensor sites in this study. On average, across a baseline and five phone-call deployments, the sample of sensor-equipped pumps saw 7.5 breakdowns and 5.1 repairs per month (3.8% and 2.6% of instrumented pumps, respectively). The control group of non-sensor-equipped pumps saw 5.4 breakdowns and 6.3 repairs per month (2.8%, 3.2%). These incidents had minimal impact on the overall functionality of each study group, where ground-truth survey data showed average functionality rates of 43% for control-group pumps (standard variance = 0.05%) and 88% for instrumented pumps (standard variance = 0.36%).

Of the total sample in this study, 3.3% were observed to fail each month on average, and 2.9% were observed to be repaired each month. Bimonthly breakdown and repair rates were not statistically significant between the study groups, with an average of 6.5 breakdowns and 5.7 repairs each month during the study across all 390 sites.

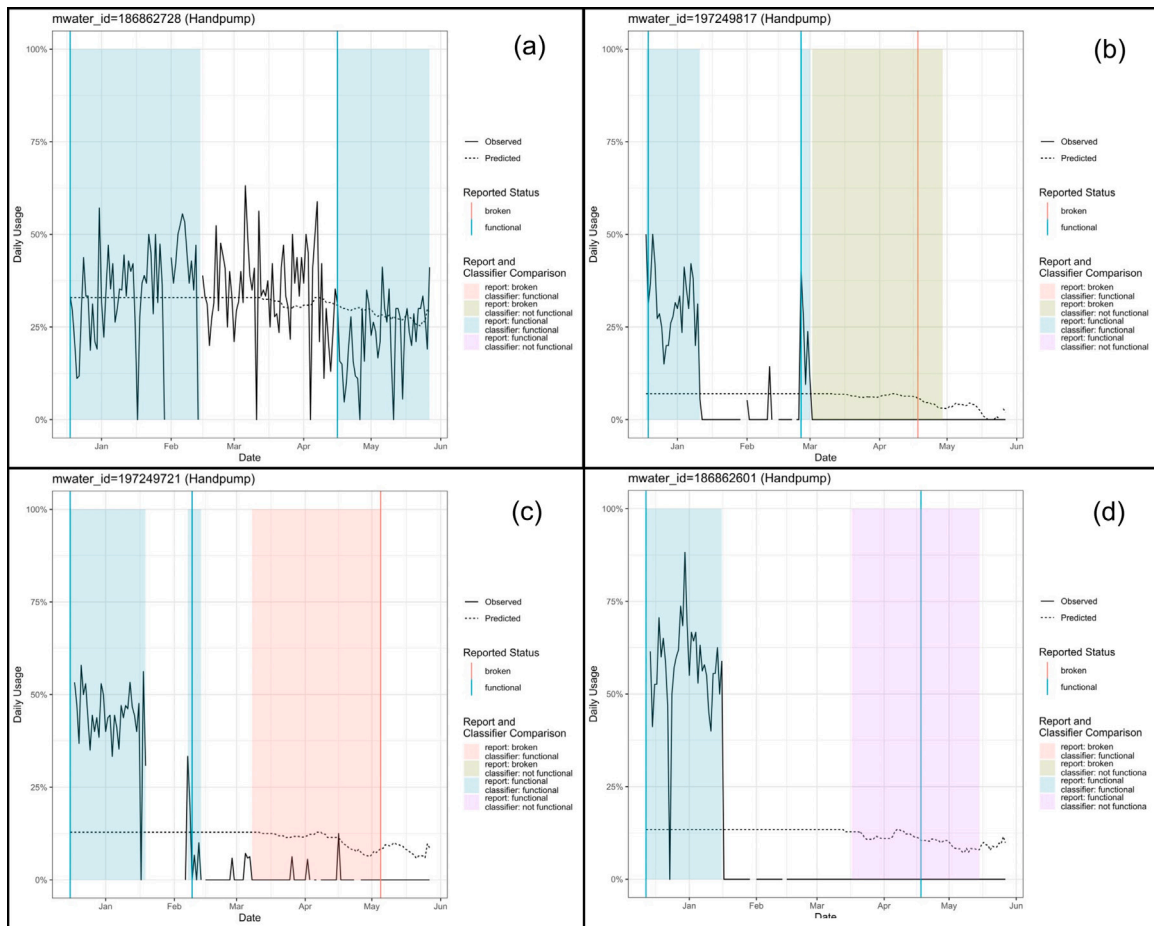


Fig. 12. Four possible outcomes of classifier functionality status assignments. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

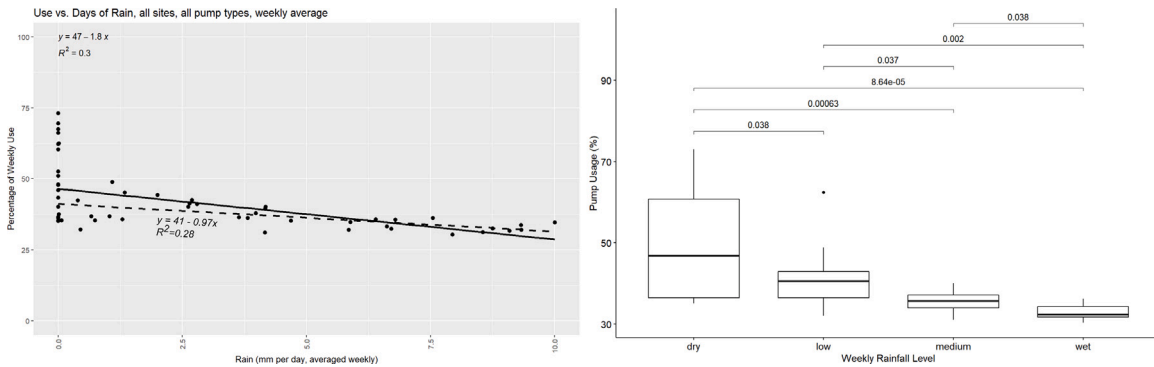


Fig. 13. For all data collected at instrumented pumps in this study, there is a decrease in average daily pump usage as a function of local rainfall (left). This impact becomes more visible when data is binned by rainfall level (right).

Identification of sites with high rates of breakdowns was flagged as a potentially useful outcome of this study from an operational perspective. Additionally, quantification of repair response times could be used to examine the efficiency of the utility’s O&M planning. At PRUWASSA’s request, an mWater-based dashboard was made available with these data presented spatially to identify geographical variations in pump usage and breakdown patterns. A few examples of these interactive data are shown in Fig. 16.

4.1.1. Pump usage patterns

Pumps instrumented in this study showed large variation in usage based on the pump type, with hand-pumps used at much higher rates

than electrical boreholes, and DC boreholes used at a higher rate than AC boreholes. Consistent overall usage patterns are visible across LGAs, which show a clear response to local rainfall. The study showed a minor decreasing trend in the usage of online, instrumented pumps.

PRUWASSA identified pump over-use as a driver of potential O&M improvements. To support identification of sites or regions with high pump usage, an mWater dashboard was made available showing pump locations and usage levels derived from sensor data. Fig. 17 shows one way to present these data to stakeholders. Additionally, monthly usage patterns were mapped on the shared dashboard to present a longitudinal summation of the data.

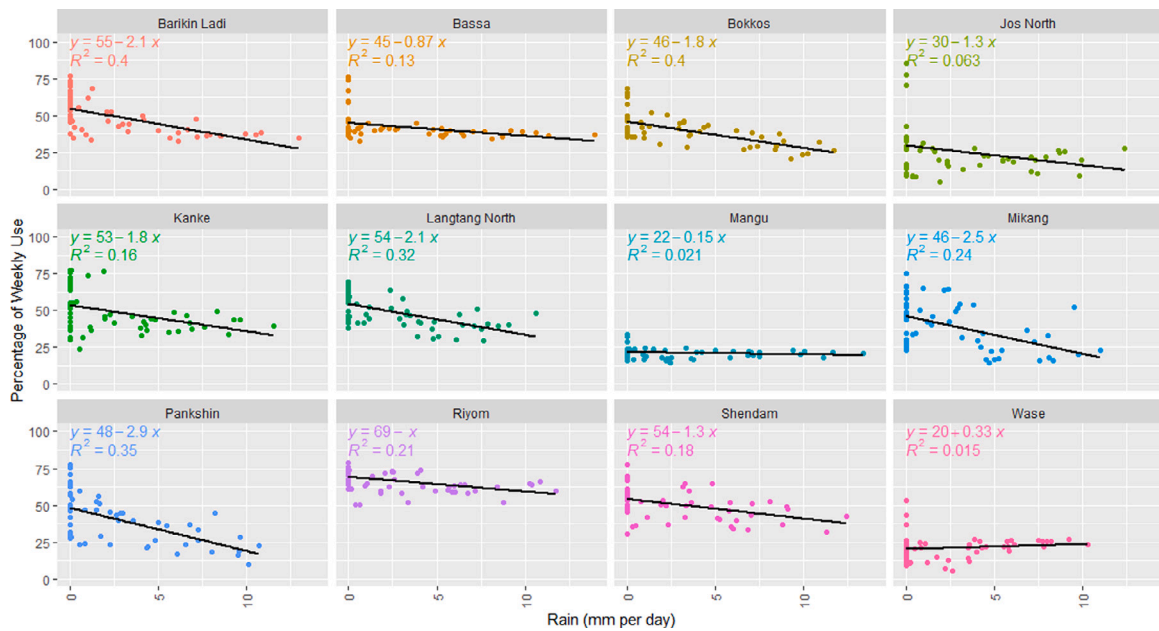


Fig. 14. Pump usage as a function of rainfall varies by LGA.

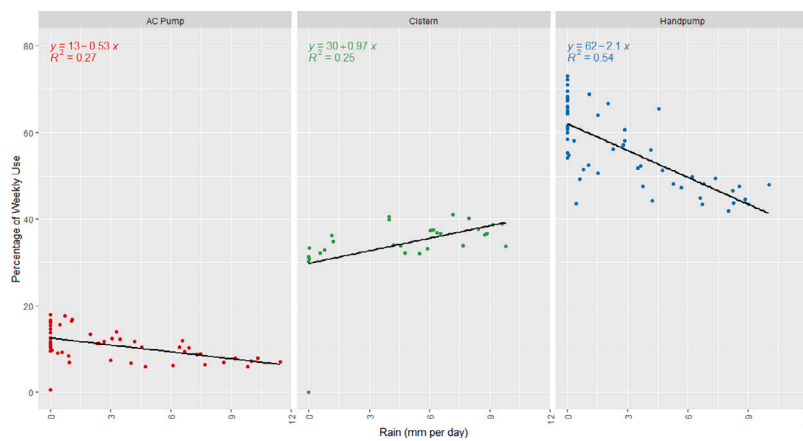


Fig. 15. The impact of rainfall on pump run-time varies by pump type.

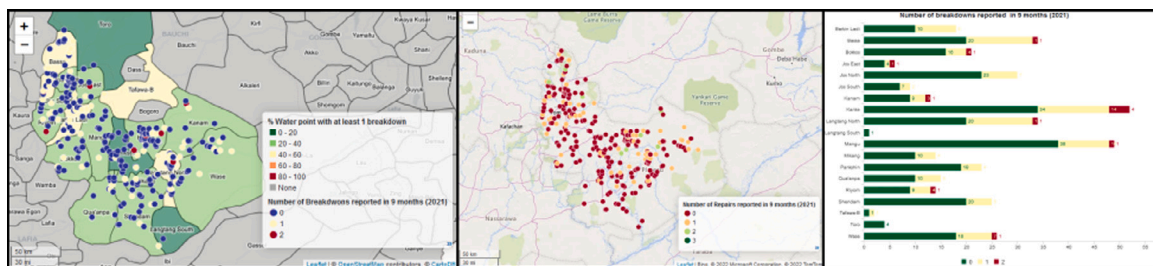


Fig. 16. An interactive dashboard presents spatial functionality, breakdown, and repair response data for use by PRUWASSA.

4.1.2. Classifier statuses and performance

Classifier statuses are derived from sensor-based run-time estimates and remote-sensing rainfall data. These provide a more detailed picture of pump usage over the course of the study year, showing variations that are invisible in monthly sampling regimes.

One difficulty in matching classifier statuses to “Non-functional” ground-truth statuses results from ambiguous changes in pump usage. This also helps explain the low specificity of the classifier. High levels of rainfall are often interpreted as driving non-use of a pump, where in

reality the pump might be broken. A calibration experiment in which the “Seasonal Disuse” classifier status was scaled down and replaced with “No Use” shows that adjusting the sensitivity of the classifier to rainfall offers a closer match with ground-truth functionalities. Specifically, Fig. 18 shows the result of reassigning 25% of the classifier’s “Seasonal Disuse” category to “No Use”, effectively treating these pumps as broken. Comparing classifier and ground-truth values on the closest matching dates, this reallocation resulted in a change from 6.1% functionality difference to 4.3%. Future work should draw

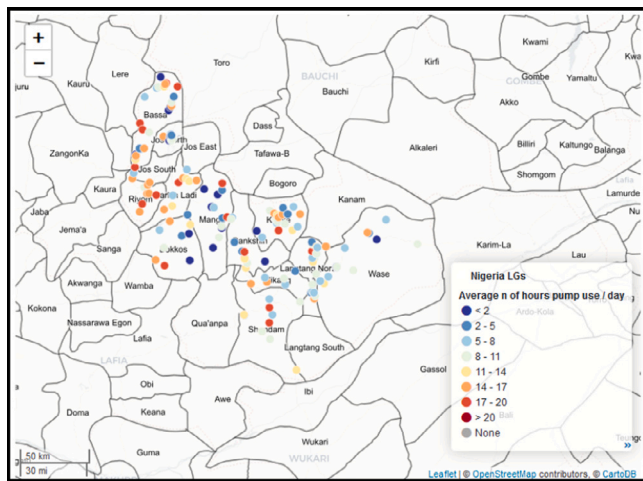


Fig. 17. An interactive dashboard made available to PRUWASSA staff presents spatial average hourly usage across all sensor-enabled sites.

Table 6
Results of handpump usage threshold adjustments.

Threshold cutoff	1000	1500	2000	2500	5000
Overall accuracy	96.1%	94.6%	94.5%	93.4%	89.0%
Bias (mean difference)	2.9%	1.5%	1.5%	0.5%	-3.7%
True positive rate (Sensitivity)	99.5%	98.0%	97.9%	96.8%	92.3%
True negative rate (Specificity)	12.5%	12.5%	12.5%	12.5%	22.2%

on additional features to calibrate the impact of rainfall on pump usage in order to better classify pump statuses, potentially including previous activity patterns before the onset of rain events to more accurately identify seasonal disuse.

Another weakness of the classifier algorithm is an assumed heterogeneity of hand-pump usage with respect to sensor data. As it stands, hand-pump functionality or non-functionality is determined by interpreting any 40-minute period of hand-pump use above a certain threshold as “In Use”, and below that threshold as “No Use”. For each of these periods, the number of either reed switch events or vibration switch events is summed and compared to this threshold, which was set to 1,000 by default in order to filter out, for example, unsuccessful pump use events. A brief optimization experiment was carried out to examine the impact of threshold modification. The results are shown in Table 6.

Modification of the original threshold improved the model’s specificity, even when applied across the entire sample of hand-pump sensors. These results indicate that calibration of this threshold could improve the model’s performance in identifying functional hand-pumps. Future work could use a threshold specific to each hand-pump to calibrate individual, site-specific functionality and non-functionality, possibly based on periods of known use immediately following instrumentation.

4.1.3. Seasonality patterns

Based on prior research, a decrease in groundwater use in response to increased local rainfall is unsurprising. It has been posited elsewhere that populations which rely on boreholes often turn to surface water when it is available (Thomson et al., 2019). This is an important consideration given changes in precipitation trends expected from climate change, which will impact both water-table levels and human behavior (Dey et al., 2020; Nyakundi et al., 2015). Foreknowledge of these patterns can improve service levels and public health, since a community turning to surface water for drinking-water needs can nullify the health benefits of seasonal access to fossil or piped water supplies. Models of the hydrological impact of rainfall on groundwater levels could be improved by including human behavior.

One surprising finding from this research is an unexpected increase in pump usage as a function of increased rainfall in the case of the DC pumps. Meetings with PRUWASSA and other partners resulted in possible explanations for this phenomenon. First, DC pump infrastructure is more accessible during the rainy season, making it preferable to hand-pumps. Second, even at times of lower demand, when surface-water access increases, many DC systems have automatic controls that keep the cistern full as long as there is sunlight to power the pump. Therefore, no time is required to prime the pump, and water can be immediately drawn from the tap.

This seasonality response varied considerably across the LGAs in this study, suggesting that populations even within a single state responded differently to changes in rainfall. This variation could be due to geographic features, including accessible surface-water sources. Feedback from local PRUWASSA and WAN staff identified several features that might explain this variability, specifically in LGAs that saw little seasonal response. Mangu is a low-level region, surrounded by mountains that produce springs, leading to year-round spring water availability. The population generally uses this surface water, so their daily habits might depend less on rainfall. Wase is an agrarian community, and water facilities are positioned far from residential areas. Additionally, the groundwater in some areas of Wase are contaminated with heavy metals, which impacts the taste of the water and discourages its use. As such, the population might depend less on the instrumented facilities in general. These hypotheses are supported by overall low levels of usage in these two LGAs, independent of rainfall, with pump usage generally falling below 25%.

In this study year, pump usage responded significantly to seasonal changes. Future work could examine whether this behavior is consistent from year to year, which could have significant implications for drought management.

4.2. Challenges and constraints

A number of challenges impacted this study, including travel and communication restrictions caused by the COVID-19 pandemic, mechanical challenges related to pump geometry changes over time, theft and vandalism impacting hand-pump sensors, and solar resource issues with the smaller panels installed with the hand-pump sensors. Cellular connectivity was also frequently interrupted during rainy months, making recurring phone calls more challenging.

4.2.1. COVID-19

Significant obstacles were introduced by the onset of the COVID-19 pandemic, which impacted the design and deployment processes in this project. We previously described a theory for product design for service providers (Sharpe et al., 2019), and the pandemic altered the tools by which project stakeholders could communicate, placing even greater emphasis than usual on the importance of collaborators in the design process. Crucially, the primary designers of the products described in this study were unable to directly access the infrastructure on which the products would be deployed. This resulted in sub-optimal product performance, but also highlighted the potential utility of long-distance communication tools in supporting successful product design.

The COVID-19 pandemic required a radical departure from the typical approach to deploying this study. Instead of on-the-ground engagement by staff versed in the sensor technologies, this project engaged local water system experts, and NGO and government staff trained remotely in sensor installation and data collection. This approach had the advantage of building independent capacity among government and NGO partners in Nigeria. Furthermore, remote communication enabled a participatory approach to sensor design, training, installation, and data collection, which included local expertise to a greater degree than might have occurred had foreign engineers made local determinations on-site.

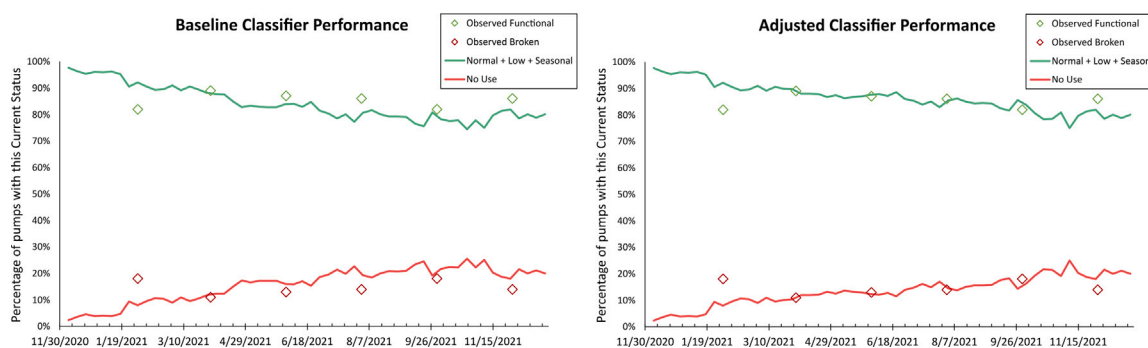


Fig. 18. The classifier initially overestimates broken pumps during most months (left). Manually applying a 25% reallocation of “Seasonal Disuse” categories to “No Use” results in a closer fit to observed functionality data across the sensor-enabled sample (right).

4.2.2. Mechanical sensor failures and O&M

As with any piece of operating equipment, some sites require constant minor sensor repair and upkeep due to normal wear and tear, especially at high-use water facilities. These include replacing broken wires or tightening loose mounting screws. Other repairs are less frequent and require site visits by WAN staff.

More significant repairs are generally required at high-use sites. There are a few mechanisms for these. First, at sites with very high use, loading on the electrical components can cause batteries to become displaced, connectors to disconnect, or even mechanical failure of PCB components. These issues can often be resolved by visiting the site, opening the sensor, and resetting its power supply. Second, sites with very high use often see minor mechanical failures in pump components, such as worn-out bearings. This has downstream effects caused by geometric changes in the pump that can disrupt the sensor input or even damage the sensor system. Designers of hand-pump monitoring systems should be aware of the potential for significant mechanical and tolerance changes caused by use, especially by bearings wearing down and changing the pump handle’s location and range of motion.

4.2.3. Representativeness of sensor sites

One significant constraint in this study was the requirement that all sensor sites be functional at the time of sensor installation. This requirement was imposed because: (1) it was expected that this might be required in order to observe enough pump breakdowns to make meaningful claims about the algorithm’s True Positive rate; and (2) it was unknown whether existing broken pumps would see repairs during the study period. The result of this constraint was a significant difference in functionality between sensor equipped test sites and non-equipped control sites.

5. Conclusion

This study was designed to establish whether sensor-based monitoring of rural water infrastructure could be accurate and effective in representing system-wide water pump functionality and use.

Data processed from the year of sensor and survey observations was incorporated into an interactive dashboard made available to PRUWASSA to support planning and management activities. This dashboard includes detailed asset inventory data for all sites, observed pump failures and repairs over time based on ground-truth phone calls, and repair times for all 400 study sites. For sensor-equipped sites, average hourly usage and other spatial and longitudinal data are presented.

We evaluated three questions:

(1) What are the operating characteristics and trends of these different kinds of water pumps?

On average, hand-pumps are operated for 13.5 h per day, while AC pumps are operated for 2.5 h per day. Both hand-pump and AC electrical pump usage decreases as rainfall increases. In contrast, DC

pump powered cisterns operate for an average of 8.4 h per day, which increases during the rainy season.

(2) Can water-point functionality be predicted with electronic sensors?

Sensor-derived functionality predictions were compared to ground-truth data collected with site visits and phone calls. While the ability to detect running pumps was relatively high (94.4% sensitivity), the ability to correctly identify broken pumps as broken was much lower (25.0% specificity). This is largely due to difficulties involved in identifying a pump that is actually broken versus a pump that is currently not being used. Overall, the classifier used in this study overestimated the influence of seasonality on pump usage. Future work should improve these methods to determine what pumps are seasonally disused or actually broken.

(3) Does the instrumented water-point sample accurately represent average water system functionality across the region?

Sensor-installed sample pumps compared to a random sample of other water pumps in Plateau State varied in terms of overall functionality, averaging 43% for control sites and 88% for sensor sites. This is unsurprising as inclusion criteria for the sensor-installed sites included day-of functionality.

However, over the course of the 12-month study period, breakdown and repair counts were found to not be significantly different, with 3.3% of sites on average failing each month and 2.9% on average being repaired each month.

The high overall accuracy of the sensor–diagnostic system and the demonstration that sensor-instrumented sample sites can represent population-level breakdown and repair frequencies, suggests a utility of this technology to support sample-based monitoring of overall water pump operation and water volume delivery. However, the poor performance of the system in distinguishing between broken and unused pumps will limit the ability to use these technologies to trigger repair activities at individual pumps.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Evan Thomas reports financial support was provided by The World Bank. Taylor Sharpe reports a relationship with Virridy that includes: employment. Evan Thomas reports a relationship with Virridy that includes: employment and equity or stocks. John Feighery reports a relationship with mWater that includes: employment. Emmanuel Iorkumbur reports a relationship with WaterAid Nigeria that includes: employment. Ellen Greggio reports a relationship with WaterAid Nigeria that includes: employment. Luis Andres reports a relationship with The World Bank Group that includes: employment.

Crystal Fenwick reports a relationship with The World Bank Group that includes: employment.

Data availability

Data will be made available on request.

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Major stakeholders include the Plateau Rural Water Supply and Sanitation Agency (PRUWASSA), Local Government Areas' (LGAs) WASH Departments, and the Community and Social Development Project (CSDP). PRUWASSA was a focal partner involved in all project stages and activities, including sensor installation and data collection. The consultants organized and led consultations, training, and workshops with principal project stakeholders.

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