Groundwater Monitoring Using Handpump Vibration Data for Rural Africa

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Abstract

We present a novel technology for monitoring changes in aquifer depth using handpump vibration data. This builds on previous work using handpump movement data to track handpump usage and facilitate handpump maintenance systems in rural parts of Kenya. We aim to develop a cost-effective and scalable infrastructure to monitor shallow aquifers in regions where handpumps are already part of water infrastructure, but where traditional sources of groundwater monitoring data may be limited or non-existent. Data was gathered from accelerometer sensors attached to the handle of nine handpumps in the study site, instrumented for a year. Results show handpump vibration data modelling may provide useful aquifer monitoring information to complement existing hydrogeological modelling.

1 Introduction

Groundwater is directly linked to United Nations' Sustainable Development Goal 6 (SDG 6) - clean water and sanitation for all by 2030 (1). It is estimated that groundwater provides around 50% of all drinking water and 40% of all agricultural irrigation worldwide (2). In Africa, groundwater is the major source of drinking water and its use for irrigation is expected to increase substantially to tackle growing food insecurity (3).

The magnitude of groundwater's significance is in sharp contrast to the dearth of reliable quantitative information on groundwater resources (1; 3; 4). Long-term monitoring data are often scarce in Africa, and wherever data are available, inconsistencies in methodologies make comparisons difficult (5; 6). Since traditional groundwater monitoring technologies (7; 8; 9) are often resource intensive, recent efforts have shown remote sensing observations can provide useful auxiliary data to improve global groundwater estimates (5). We propose a shallow aquifer monitoring technology that utilizes the continent's existing handpump infrastructure. Handpump remains a reliable and low-cost method to access groundwater in the context of rural water supply for around 200 million people in Sub-Saharan Africa (10). We aim to explore if a network of these handpumps can provide information that can be exploited using machine learning approaches to monitor the underlying shallow aquifer systems.

Previous efforts showed that vibration data at the handpump's handle are indicative of pump malfunction (10; 11). Changes in the characteristics of vibration data, potentially due to handpump malfunction, can be tracked using novelty detection approaches. Remote transmission of these novelty scores, as part of a handpump maintenance infrastructure, can be used for rapid pump maintenance. The vibration data were also shown to be indicative of changes in the water level at the borehole under controlled circumstances (12; 13). These works showed that the vibration generated at the handpump's handle are affected by the weight of the system, i.e. the mechanical weight and the volume of water inside the rising main. The variation in vibration characteristics was exploited to estimate the water level at the borehole of the handpump. We aim to determine if vibration data obtained from community handpumps in an unconstrained real-world setting can be used to track

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AI for Social Good workshop at NeurIPS (2019), Vancouver, Canada.

long-term changes in aquifer level (a conditional yes), and if the results generalize across different depths of shallow aquifer systems (yes).

Related efforts (14; 15; 16; 17; 18; 19; 20; 21) show the potential of using machine learning to predict long-term changes in aquifer level based on hydro-climatic data (e.g., rainfall, temperature) in areas where hydrogeological data are difficult or expensive to obtain. The proposed framework is novel because (1) it uses handpump vibration data to model changes in water level, and (2) it combines regression approach with novelty detection approach to develop a novel shallow aquifer monitoring technology that is designed to work alongside a handpump maintenance infrastructure. The framework can also be extended to incorporate hydro-climatic data or outputs from hydrogeological models.

2 Methods

We use a regression model to learn a mapping function from vibration data to water column. The proposed framework (Fig. 1) is designed to work alongside a handpump maintenance infrastructure (11), represented by dashed lines and not part of the framework itself. The community handpumps are often regularly used and tend to break down once every few months on average. Depending on the severity of malfunction and the type of subsequent repair, the characteristics of vibration data may change substantially, affecting the outputs of regression model. The vibration data may also change when the water in the borehole reaches previously unobserved levels. During such circumstances, the novelty scores may also serve as a guideline to indicate the confidence in the regression model's outputs, where higher novelty scores would correspond to lower confidence in the model's outputs. When the vibration data has changed due to a pump repair, a simple solution to continue using the same regression model may be to calibrate the post-repair vibration data back to the pre-repair data. The calibration may be performed using a regression model by assuming the vibration data averaged over few days pre vs. post repair are the same.

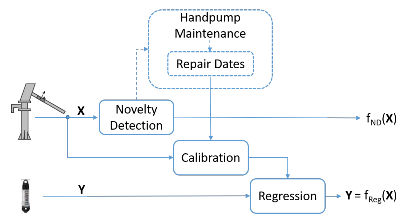


Figure 1: Framework.

2.1 Study Area and Sample Selection

The study area is located in Kwale County, Kenya, south of Mombasa and adjacent to northern Tanzania. The area includes the long-established coastal tourism industry in Diani and the more recent mining and commercial sugar production industries. To sustainably manage the resulting competition for water resources, reliable data on groundwater is vital (22; 23). To test if the model generalizes to handpumps drawing water from different depths, three different monitoring sites are selected corresponding to three depth ranges - shallow, medium, and deep, where these categories are arbitrarily defined based on available samples.

2.2 Long Short Term Memory (LSTM) networks

Since we wish to provide temporal context to model water column data in terms of past examples of daily handpump vibration data, LSTMs constitute a suitable model for our application. Different variations of LSTMs have been successfully implemented in many fields (24; 25; 26; 27; 28). Given

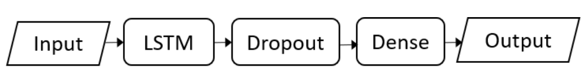


Figure 2: A flowchart of LSTM architecture.

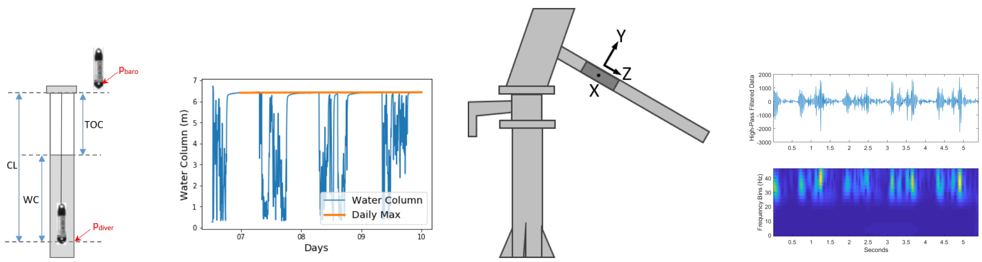
the relatively small size of the training data, we opt for a simple neural network architecture, consisting of a LSTM unit, a drop-out unit, and a dense layer in sequence (Fig. 2). As more data become available in future, there are opportunities to implement deeper (e.g. stacked layers) and other variations (e.g. shared layers) of networks. The model parameters (learning rate $[10^{-2} - 10^{-5}]$, number of hidden nodes $[50 - 200]$, epochs $[10 - 200]$, batch size $[10 - 50]$, and input time steps $[1 - 14$ days$]$) were coarsely optimized using separate training and validation sets with (80-20%

splits). A separate test set (one-third of data) was held out for evaluating the trained model. The dataset was split sequentially in time (from past to future) to reflect a real implementation scenario.

2.3 Novelty Detection Approaches for Condition Monitoring

Novelty detection approach (29) is applicable to condition monitoring of handpumps because usually compared to “normal” handpump operations, there are very limited examples of “abnormal” handpump operations (e.g. broken seal, valve or handle malfunction, etc.). We use Gaussian Mixture Model (GMM) (30) to learn a normal model based on vibration data during normal operation. An appropriate number of the mixture components is determined based on the data by using Dirichlet process mixtures (31). Given this model, the inverse of the log-likelihood of examples can be considered as novelty scores, i.e. lower the log-likelihood, more novel the examples. Since GMM provides probabilistic novelty scores, it is suitable for our application where we intend to use the novelty scores as a measure of confidence of the regression model’s outputs.

3 Data



(a) (b) (c) (d)

Figure 3: (a) Diver sensor installation (adapted from (32)), (b) typical variation in water column, (c) accelerometer sensor installation, and (d) data preprocessing (top) and feature generation (bottom).

Fig. 3 shows respectively diver sensor installation, typical water column data, accelerometer sensor installation, and vibration data preprocessing (top) and feature generation using morelet transform (bottom) for a temporal window. A daily average of these temporal windows along with the corresponding daily maximum water column represent a feature-label pair. A collection of these feature-label pairs per handpump constitutes a training dataset for that handpump. Wherever feasible, we use Gaussian Processes (33) to impute frequency features corresponding to missing days.

4 Results

We only report results for one example handpump from each of the three depth categories. In Fig. 4, the top row shows the log-likelihood of training (blue dots) and test (red dots) examples given the normal model. The examples in future incrementally appear to be more different from the normal examples. This trend is expected because the vibration data is expected to change over time either due to gradual pump wear and/or change in water level in the borehole to previously unobserved levels (a relatively smooth change), or due to severe pump malfunction and subsequent repair (a relatively abrupt change). Many repair-related abrupt changes stand out visually, and are aligned to their corresponding pump repair dates (black dashed lines), whenever such records are available.

The bottom row in Fig. 4 shows the LSTM estimates for training, validation, and test sets in blue, orange, and red colours respectively in terms of their 95% confidence interval based on 10 iterations of training LSTM model with random initialization. Generally, vibration data are indicative of changes in water column for most handpumps. Pump repairs change the vibration data features substantially, which when “corrected" via calibration, does somewhat help to improve water column estimation. But the frequency and/or the nature of repairs may affect the effectiveness of the calibration. Nevertheless, the novelty detection outputs provide a reasonably accurate guideline to determine when to trust the regression model outputs. Typically a drop in the log-likelihood corresponds to either an inaccurate water column estimate or one with high uncertainty.

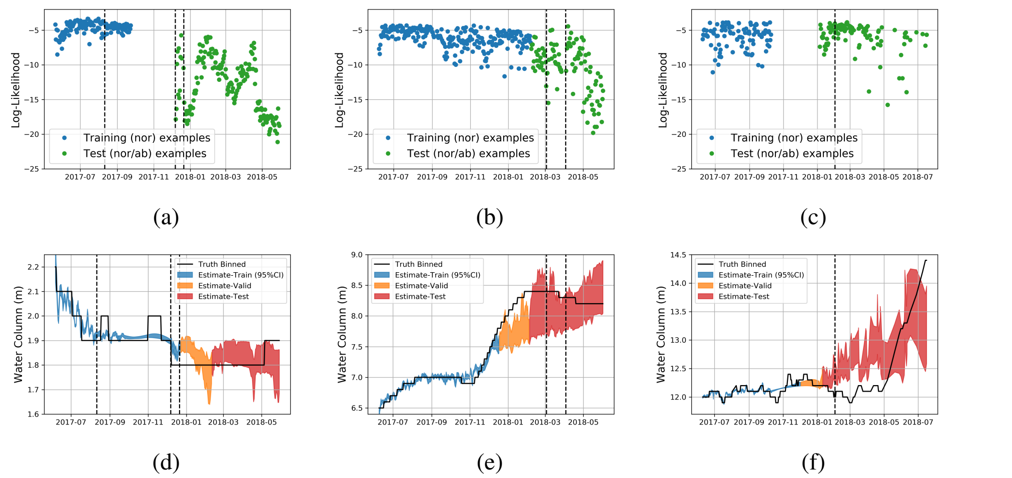


Figure 4: Log-likelihood of examples given normal model (top row) and water column LSTM estimates LSTM (bottom row). Columns correspond to a shallow, a medium, and a deep handpumps.

The proposed technology is intended to be implemented at scale by concurrently modeling a network of community handpumps to approximately infer the trend in the shallow aquifer water levels. When we plot the fractional change in water columns at one particular (medium-depth) monitoring site with respect to a common reference date (Fig. 5), results show the estimated changes in water column approximately track the true trend. However, the estimates deteriorate as we start predicting further ahead in time due to the current limitations in the model.

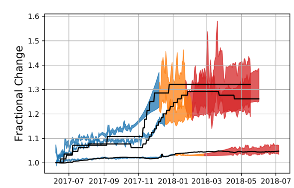


Figure 5: Fractional change in water column in medium-depth handpumps.

5 Discussions

As expected, going from constrained to unconstrained real-world application brings challenges. In terms of hydrogeology, one year of data is not sufficient to track long-term changes in aquifer level. In current dataset, validation and test data are often very different from training data, complicating both training and testing the model. Since 15% of data were missing, the accuracy of the imputed data degrades as the duration of missing data increases. The vibration data calibration becomes less effective as the number and/or severity of breakdowns/repairs increase. A more principled solution may be to use transfer learning (34; 35). Further experiments are required to determine if transfer learning is feasible, and how much new data (hours-days) are required to properly re-train the post-repair model. There are also opportunities to model multiple handpumps simultaneouly and fuse hydro-climatic data, and wherever available, outputs from hydrogeological models using multi-task learning extensions of LSTMs (36; 37).

Due to the current limitations, there are risks of misinterpreting inaccurate water column estimates. The novelty detection outputs may somewhat help to mitigate these risks by indicating the uncertainty in the water estimation outputs. Although the monitoring data is intended to assist sustainable groundwater management among competing users (e.g. community vs. industry), incompetent management poses risks to vulnerable population. The data may also unintentionally induce forced migration of households out of areas rich in groundwater resource. Hence, a successful implementation of this technology relies on both adequately training local experts as well as ensuring sound groundwater governance. Given the increasing global importance of groundwater monitoring data, novel cost-effective technologies that utilize regional available infrastructure may help bridge the gap between the available state-of-the-art but cost-prohibitive technologies and the capacity of resource-constrained nations to adopt them.

Acknowledgments

The authors would like to thank FundiFix, Rural Focus Ltd., Base Titanium Ltd., and the Kwale Country Government. This research was funded by the UK Government via NERC, ESRC, and DFID as part of the Gro for GooD project (UPGro Consortium Grant: NE/M008894/1).

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