A Data-Driven Approach to Soil Moisture Collection and Prediction

Using a wireless sensor network and machine learning techniques

Zhihao Hong , Z. Kalbarczyk , and R. K. Iyer
Electrical and Computer Engineering Department
University of Illinois at Urbana–Champaign
Champaign, USA

Abstract*—Agriculture has been one of the most under-investigated areas in technology, and the development of Precision Agriculture (PA) is still in its early stages. This paper proposes a data-driven methodology on building PA solutions for collection and data modeling systems. Soil moisture, a key factor in the crop growth cycle, is selected as an example to demonstrate the effectiveness of our data-driven approach. On the collection side, a reactive wireless sensor node is developed that aims to capture the dynamics of soil moisture using MicaZ mote and VH400 soil moisture sensor. The prototyped device is tested on field soil to demonstrate its functionality and the responsiveness of the sensors. On the data analysis side, a unique, site-specific soil moisture prediction framework is built on top of models generated by the machine learning techniques SVM (support vector machine) and RVM (relevance vector machine). The framework predicts soil moisture n days ahead based on the same soil and environmental attributes that can be collected by our sensor node. Due to the large data size required by the machine learning algorithms, our framework is evaluated under the Illinois historical data, not field collected sensor data. It achieves low error rates (15%) and high correlations (95%) between predicted values and actual values across 9 different sites when forecasting soil moisture about 2 weeks ahead. Also, it is shown that the prediction outputs can remain accurate over a long period of time (one year) when reliable data are fed to the model every 45 days.

Keywords: data-driven; precision agriculture; soil moisture; machine learning.

I. Introduction

The average farm size in the U.S. is increasing every year despite a continuously decreasing farmer population [1]. As a result, more and more cropland is shifting to large farms. Large farms rely on a more structured and automated management system to realize better financial returns and use of resources.

Precision Agriculture (PA) promises to deliver the next generation of agriculture by actively using technology to collect various types of data and applying site-specific, sensor-based treatment to the farm. As the world moves into the era of the Internet of Things (IoT), data are collected in various forms from different types of devices. A unified platform is needed to ensure that the data formats are consistent and that data are readily analyzable. Once data are collected, data mining techniques can be applied to extract patterns and build estimation and prediction models that are valuable to farm management. Data-driven agriculture is still at an early stage of development and faces many challenges. As pointed out in [2, 3, 4], the major problems for PA to become reality include:

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- Crop management decisions and data collection systems need to be designed to meet the needs of specific farms.
- Automated and user-friendly systems need to be developed for users with less software experience.
- The introduction of expert knowledge must be possible. Systems should allow the inclusion of new automated methods for user-defined terms.
- Devices need to be affordable and scalable for large farm deployment.

In this paper, we designed and implemented a soil moisture collection and prediction system to address parts of the above problems using a data-driven approach. The success of the data-driven approach depends on two factors: 1) the quality of the data gathered and 2) the effectiveness of its analysis and interpretation. By using a wireless sensor network and machine learning techniques in collection and prediction respectively, an integrated system focused on soil moisture is presented. Soil moisture, a key factor in the crop growth cycle, is selected as an example to demonstrate the effectiveness of our data-driven approach. Soil moisture is a preferable target for using data-driven methods, since large volumes of data related to soil moisture and climate have been collected for decades and are easy to retrieve. We build a smart wireless device that can collect fine-grained soil moisture and related meteorological data. Two regression supervised machine learning algorithms—support vector machine (SVM) [5] and relevance vector machine (RVM) [6]—are used to show the effectiveness of data-driven tools of building soil moisture prediction model by using the same attributes that can be collected from our hardware devices.

The paper is organized in the following manner: In Section 2, we provide a system overview of our work. In Section 3 and 4, we present the detailed design of the collection and prediction, respectively. In Section 5, the proposed framework is evaluated under historical data. In Section 6, we discuss the body of related work, and Section 7 includes our future work.

Our work makes the following contributions: 1) a data-driven methodology on soil moisture is proposed to address some of the current problems in Precision Agriculture. 2) We prototype a reactive wireless sensor node that can capture soil moisture dynamics. A framework is proposed to let users easily configure the device to be site-specific. The prototyped device is tested on field soil to demonstrate its functionality and the responsiveness of the sensors. 3) We present a unique soil moisture prediction framework. The proposed framework is built on basic models generated by the SVM and the RVM algorithms and evaluated on Illinois statewide historical soil moisture dataset.

II. SYSTEM OVERVIEW

Fig. 1 shows an overview of the system, which can be separated into two parts: collection and prediction. The design principle is to create a framework that allows users to easily configure the system to be site-specific.

A. Collection System

In the collection system, a wireless sensor node is prototyped that implemented our proposed framework for sensing soil moisture and other meteorological data. The sensor node is an intelligent reactive device that focuses on collecting soil moisture dynamics data with respect to surrounding environment changes. Programmed under open source platform TinyOS [7], the node can be easily reconfigured. It offers two user-defined variables regulating the level of data granularity and sample intervals. The wireless sensor node can be used for applications such as in-field soil moisture collection and other kinds of remote site data collection, since it is specifically designed for applications that require a long lifetime.

B. Prediction System

A prediction system is built on top of the machine learning models to predict soil moisture *n* days ahead. The models predict the soil moisture value based on meteorological parameters including temperature, humidity, wind speed, solar radiation, precipitation, and soil temperature together with previous days' soil moisture values. The sparse and well-studied machine learning techniques SVM and RVM are applied on the historical data to derive mathematical models. Designed from a Precision Agriculture perspective, the site-specific model is able to incorporate data from other sources at the granularity of one day. The feature of taking user-provided data makes the system more robust by allowing the model to interact with human knowledge or reliable soil moisture data from other sources at fine granularity. Due to the large data size required by the machine learning algorithms, field-collected data from our sensor node are not used in our prediction experiments. However, the soil and meteorological attributes collected from the hardware devices are the same attributes that are used for deriving prediction models.

C. Data Source

The data used in this paper are from the Illinois Climate Network (ICN) [8] program, which monitors weather and soil conditions at 17 different locations across Illinois. Out of 17
数据源 sites, 9 low-error-rate sites are selected as our data source sites. ICN program offers soil moisture data with hour granularity and meteorological data with day granularity. Both soil moisture and meteorological raw data are preprocessed and manually examined to ensure they are error-free and well formatted.

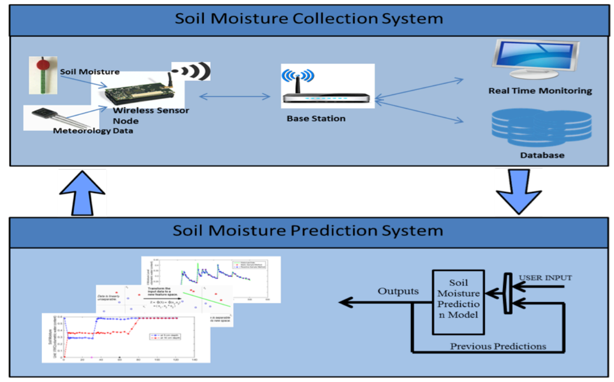

Figure 1. System overview

III. COLLECTION SYSTEM DESIGN

The objective in the collection system is to prototype a wireless device that can efficiently collect soil moisture and related environmental data needed for training prediction models. Compared to previous work [9,10,11], our sensor node has two distinctive features: 做的工作一定要有亮点和创新点（与之前已有的工作相比）

- **Reconfigurable Devices** provide a framework in which user-defined variables can be easily applied to configure different applications on an open source platform.
- **Reactive Sensing** extends the lifetime of the system by reactively sensing data based on environment changes.

A. Reconfigurable Device

Two variables, *maximal sample interval* and *level of granularity*, are introduced in our framework to configure device to be site-specific in order to better meet individual application requirements. The *maximal sample interval* is the largest sample rate that a node can hold. If the soil moisture values stay the same, sensors continuously monitor soil at the *maximal sample interval* rate. The *level of granularity* specifies the threshold value, which triggers the sampling rate adjustment algorithm in the reactive sensing part. It can be understood as the level of sensor sensitivity to environmental changes. The open source feature of the TinyOS platform makes the porting device code much easier.

Analysis results from historical data can be used to determine these two user-defined variables based on application requirements. For example, analysis on hourly data that last two years long at one of the ICN sites shows that it takes 44 hours on average for soil moisture to have a variation greater than 0.04 Volumetric Water Content (vwc) at 5cm depth. If one is interested in collecting data at granularity 0.04 vmc or above, the device can be easily configured to take samples at 10-20 hours instead of shorter intervals to save energy while preserving data quality. Statistical methods such as linear interpolation can further compensate for the loss of data granularity. 类似于之前的降雨量测量周期调整，当降雨量长期为0时，便增大测量周期，这里利用到了历史数据进行分析。

B. Reactive Sensing

Another feature of the sensor node is that it can self adjust its sampling frequency based on surrounding parameter changes to best capture "interesting" data points. Unlike other sensor applications in which the sensor samples at a high frequency (several samples per second), the soil moisture content in a wild field does not change much on an hourly basis, especially in non-rainy days.

In our design, the decision of whether to adjust the sample frequency is based on the difference between previous soil moisture readings and current readings. The intuition behind reactive sampling is that when soil moisture varies, it is likely raining or during a rainy period that can last a few days. If the difference exceeds some pre-set threshold, it is likely a rainy period at monitoring locations. In response, the sample intervals are exponentially decreased to a much shorter sample window to capture the variations. Once the soil moisture readings become stable, the sample intervals start to increase linearly until the maximum sample interval is reached.

C. *Preliminary Hardware Test*

Our design is prototyped on a MicaZ [12] node with a MDA300CA [13] data acquisition board. An experiment was conducted on the field soil to test the responsiveness of our sensor and functionality of the sensor network. In the experiment, two VH400 [14] soil moisture sensors were attached to the sensor node and buried completely under the ground surface at 5 cm and 10 cm depths. The soil sample was taken from an open cornfield and transferred to a bucket container. The hardware was configured such that the *maximal sample interval* was 40 seconds and the *granularity level* was 0.08 vwc. The adjustment of the sampling interval was based on the reading at the 5 cm depth. The experiment lasted an hour in a lab setting, and results are shown in fig. 2.

The red line (star) represents the soil moisture readings at 10 cm, and the blue line (circle) represents the readings at 5 cm. The first readings from both sensors are errors due to sensor warm-up stages. At point 30 (indicted by magenta diamond), a small volume of water was poured into the bucket. At point 60 (indicated by black upward-pointing triangle), a large volume of water was poured into the bucket.

The sensor node was able to collect data at different depths and reactively adjust the sampling interval. When the small volume was poured into the bucket, only the soil at 5 cm depth was saturated with water, and soil moisture at 10 cm stayed at the same level. When a large volume was applied, the soil at both levels got saturated. On the 5 cm depth line, the frequency of sampling increases at times 5 and 35, due to our reactive algorithm.

IV. Prediction System Design

In the prediction part, we propose a soil moisture prediction framework to estimate and forecast soil moisture level over time based on meteorological data. The prediction framework is built on basic models generated by machine learning algorithms. To establish a well-performed basic model, input data are parsed from the ICN database and fed to machine learning algorithms for training and validating purposes. The inputs are meteorological data: temperature, humidity, wind speed, solar radiation, precipitation, and soil temperature, together with the previous day's soil moisture values. The output is the soil moisture value for the current day as

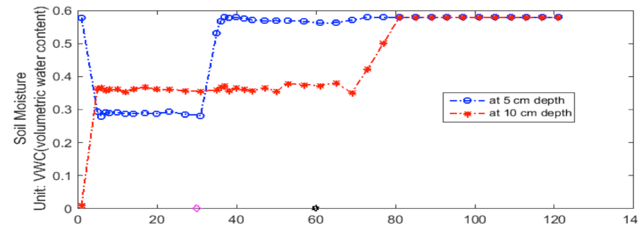

Figure 2. Sensor node on field testing

illustrated in fig. 3.

A feedback loop is built on top of the basic models to predict soil moisture in a longer time window. Output from day *t* can be fed back to the prediction system, in order to predict soil moisture at day *t*+1. As a result, running model in a feedback loop for *n* times using previous output as next iteration's input, the model predicts soil moisture *n* days ahead.

The introduction of this feedback loop model creates the opportunity for users to manipulate inputs at any iteration. At each run, the input of environmental parameters can come from forecasting values or user-provided values. The input of soil moisture can be either data from other soil moisture retrieval techniques or previous predicted values. For example, a common practice in agriculture is to predict the future soil moisture value if the drought situation stays *n* more days. By setting the precipitation value to zero, our model is able to make a prediction under the assumption that the drought condition continues.

A more reasonable prediction can be made by leveraging knowledge from other sources at input fields. In previous work [15, 16] on soil moisture prediction, the model is fixed and only can predict values *k* days ahead, where *k* is a fixed number. The prediction at day *t+k, k* days ahead is based on soil moisture values and meteorological data at day *t*, day t-1, day *t*-2, and so on. The prediction result is unreliable as it disregards the meteorological data between day *t* and day *t*+*k*. A heavy precipitation between day *t* and day *t*+*k* can make the result irrelevant and useless. With advances in weather forecasting technology, the forecasting of meteorological data has become more accurate and fine-grained, and it is available to the public. Our system is able to include meteorological data between day *t* and day *t*+*k* from weather forecasting. On the soil moisture input side, readings from other soil moisture measurement methods can be integrated to further improve accuracy. Physical measurement offers great accuracy in the cost of resources and human labor. The near absolute correct value from sensor measurement can be used as the input to correct the model, as the model result tends to "drift-away" from the ground truth after several runs. The evaluation of the

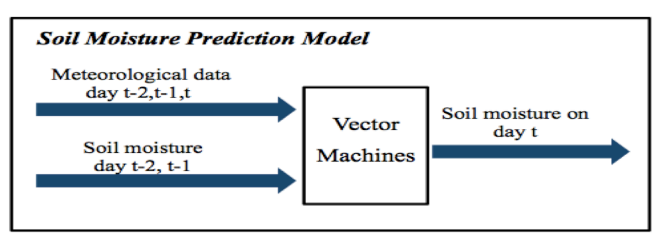

Figure 3. Basic machine learning input and output

above two methods for predicting soil moisture is presented in next section.

V. Model Evaluation

A. Methodology

After the preprocessing data, we are able to retrieve data from 9 independent sites across Illinois from 2004-01-01 to 2012-12-31. The parsed data are split based on site location so that site-specific model can be generated for each individual site. For each site, there are about 3288 data points, each representing average values of meteorological parameters for the day. The following parameters are selected as features in the machine learning process: 1) Air temperature 2) Relative humidity 3) Wind speed 4) Solar radiation 5) Precipitation 6) Soil temperature at depth 10 cm and 20 cm 7) Soil moisture at depth 5 cm, 10 cm 20 cm, 50 cm.

The data are normalized between 0 and 1 and split into testing, training, and validating data, in order to properly train the model. The following experiments are conducted on testing data that have not been used or seen by the models. The testing data include a total of 365 data entries for 2012. The rest of the data are split into training data and validation data. The ratio of training to validating data is about 80:20, a common ratio in machine learning. A radial basis kernel is used for both vector machines, and the rest of the parameters are selected based on trial and error. For training models at soil depth *d* cm, only soil moisture data at *d* cm are used as inputs. The experiment scripts are developed on top of the vector machine package provided in LIBSVM [17] and SparseBayes [18].

The metrics used for evaluating models are mean squared error (MSE), mean absolute error (MAE), and correlation coefficient (R^2). The MSE computes the average of the squares of the errors of model prediction from the actual value. MAE represents the mean value of the absolute error of the predicted value from the target value. Correlation coefficient R^2 measures the linear relationship between predicted value and actual value. R^2 can range from 0 to 1, with $R^2 = 1$ being a perfect match and 0 meaning zero correlation between the two. Equations for obtaining MSE and MAE are as follows:

$$MSE = \frac{\sum_{i=1}^{n}(t_i - p_i)^2}{n} \quad MAE = \frac{\sum_{i=1}^{n}|t_i - p_i|}{n}$$

where t_i and p_i are target value and predicted value, respectively, and n is the number of testing data points.

B. Soil Moisture Forecasting

One of the common practices in agricultural planting is to forecast the soil moisture values. In this experiment, we evaluate the performance of model forecasting aspect by predicting soil moisture content at *t+15* days, where *t* is the current date. The testing dataset is applied on the properly trained SVM and RVM model obtained by the methods described in the methodology section, given that the forecasting weather information is perfectly accurate. Table I provides the statistics of the forecasting results compared with actual values across nine different locations at depth 5 cm. The results at 10 cm and 20 cm show similar trends for forecasting up to around 20 days.

TABLE I. Soil Moisture Forecasting Result

	MSE[a](x100)		**MAE[a](x100)**		**R^2(%)**	
	RVM	***SVM***	***RVM***	***SVM***	***RVM***	***SVM***
Site 1:	0.20	0.06	3.30	1.75	82.7	85.0
Site 2:	0.18	0.11	3.27	2.63	96.1	97.2
Site 3:	0.26	0.21	3.91	3.64	93.0	94.7
Site 4:	0.49	0.12	4.15	2.42	89.3	96.9
Site 5:	0.35	0.19	4.51	3.64	94.9	98.5
Site 6:	0.18	0.22	3.30	3.25	95.5	94.5
Site 7:	0.28	0.13	4.27	2.76	93.9	97.3
Site 8:	0.33	0.09	4.15	2.13	92.6	97.4
Site 9:	0.32	0.13	4.54	2.85	92.6	97.3
AVG:	0.29	0.14	**3.93**	**2.78**	**92.3**	**95.4**

a. The statistics of MSE and MAE values are actual values times 100 for displaying.

As shown in Table I, both algorithms produce well-performed, site-specific models that capture the underlying relationship between inputs and outputs. The mean absolute errors across nine sites are around 0.039 and 0.028 for RVM and SVM, which mean the error rates are less than 15%. From the obtained average R^2 values, it is shown that there exist strong linear correlations (above 92%) between the predicted values and the actual values. Fig.4 and fig. 5 plot the performance of RVM and SVM algorithms in time-series from one of the sites. Compared with SVM, the RVM algorithm requires fewer support vectors to produce the result. The support vectors or relevance vectors used in RVM are less than 10% of total input vectors, while SVM needs about 50% of input vectors. As a result, the RVM solution is sparser than the SVM one. Even though the performance of SVM is slightly better than RVM, the difference is insufficient to consider it a better algorithm.

C. Consecutive Estimation of Soil Moisture

Aside from forecasting, another experiment is conducted on our system to evaluate its performance in making consecutive estimations of soil moisture. New estimation value will be based on previous estimation result. As a result, the values tend to "drift away" from the ground truth over long time periods.

The purpose of this experiment is to measure the model performance over long time periods (one year). Unlike

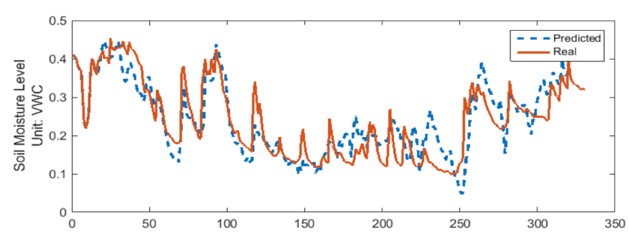

Figure 4. RVM forecasting in time series plot

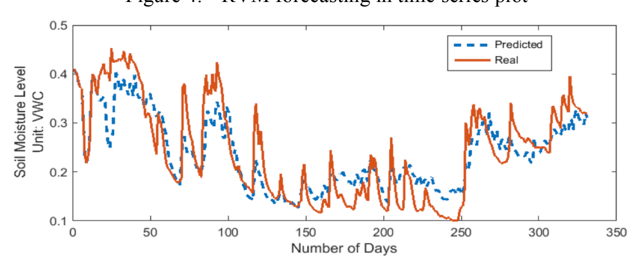

Figure 5. SVM forecasting in time series plot

hydrology study, agricultural lands are regularly managed and maintained by people. In farming practice, model-estimated values will not be the only source for monitoring soil moisture. Point measurements from sensor devices offer accuracy but are costly in terms of labor and resources.

Our system is able to reduce its estimation errors by using accurate data as inputs instead of estimated values, when accurate data become available. In this way, farmers can obtain fine-grained soil moisture data without frequently measuring it in the field. Depending on the specific application requirements for soil moisture accuracy, one may set various time intervals for correcting model-estimated values. Model-estimated soil moisture values at day t and day t+1 are used as inputs to generate soil moisture at day t+2. The evaluation statistics are obtained via comparing estimated soil moisture values with actual values on the same day. Table II lists the experimental results of soil moisture estimation models at depth 20 cm. Two strategies of estimation are tested using same trained SVM models in which method 1 (No CRT) makes consecutive estimations based on previously estimated data without correction, and method 2 (CRT) corrects data every 45 days. Results of running RVM at other depths from 5 cm to 50 cm show similar trends in performance.

TABLE II. ESTIMATION COMPARSION WITH OR WITHOUT CORRECTION

	MSE(x100)		MAE(x100)		R^2(%)	
	No CRT[a]	*CRT*	*No CRT*	*CRT*	*No CRT*	*CRT*
Site 1:	0.06	0.05	1.99	1.74	91.7	92.6
Site 2:	0.32	0.25	3.73	2.60	88.1	90.8
Site 3:	0.16	0.11	3.05	2.58	96.9	96.8
Site 4:	0.76	0.12	6.39	2.34	**78.8**	**96.2**
Site 5:	0.44	0.14	4.99	2.38	88.8	96.1
Site 6:	0.12	0.05	2.64	1.78	93.0	96.1
Site 7:	0.88	0.77	6.79	6.33	**79.0**	**93.7**
Site 8:	0.39	0.16	5.21	2.99	89.0	95.6
Site 9:	0.23	0.20	3.90	3.36	89.0	95.0
AVG:	0.37	0.21	**4.30**	**2.90**	**89.0**	**94.8**

a. No CRT means the data are not corrected during the experiment. In CRT, predicted values are corrected every 45 days.

As shown in Table II, even without correction, our models can still be responsive to the environment changes and remain fairly accurate over the course of a year. The overall average MAE is 0.043 vwc for method 1, and average correlation coefficient is 89%. Compared with method 1, method 2 shows improvements in terms of average correlation coefficient and MAE. However, it should be noted that in sites 4 and 7, the improvement gains are significant compared with other sites. Using method 2 in site 4, the MAE is reduced from 0.064 to 0.023, while R^2 increases from 78.8% to 96.2%. Based on our observations, the model can accurately follow the slope of soil moisture decay when there is no precipitation or when precipitation is small. However, a large error gap between predicted value and real value occurs when there is a sudden increase in soil moisture. This indicates that the models perform relatively poorly on days of heavy precipitation but are able to follow the decay trends of soil moisture fairly well. In practice, a dynamic correction strategy may be adopted where the models are corrected only when heavy precipitation occurs.

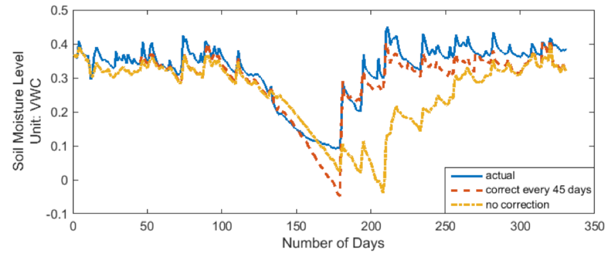

Figure 6. No-CRT and CRT perforamnce comparision at depth 5cm

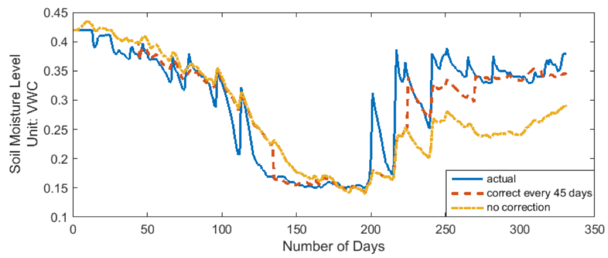

Figure 7. No-CRT and CRT perforamnce comparision at depth 10cm

Fig. 6 and fig. 7 gives visual comparisons of the performance of method 1 and method 2 at depths 5 cm and 10 cm. The solid lines represent real values in 2012 from one of the ICN sites, the dash-dot lines show the performance of the No-CRT method, and dashed lines show the performance of the CRT method. The models perform well initially, when the trend of soil moisture is decreasing. Large error gaps between predicted and actual values occur when soil moisture content has a sudden large increase in the middle of the plot. Using the correction method, the predicted value is brought back to a reasonable value in a short period of time, while the large error gaps remain until the end in the no-correction method.

VI. RELATED WORK

Existing studies and research have provided separate solutions on the collection and analysis ends. In [19], a wireless sensor network has been deployed in large fields to collect soil moisture and meteorological data. The data acquisition procedure starts every 10 min for monitoring soil moisture dynamics in the field. A reactive sensor node was developed in [20] that samples at high frequency during rainfall. On the analysis end, soil moisture modeling has been studied for decades. Soil moisture analysis includes topics on physically based modeling, data-driven modeling, geo-statistical analysis, and more. While designing physically based models requires significant in-depth knowledge of soil water and a statistics background, machine learning techniques can efficiently generate site-specific models, once the training methodology and respected dataset are set. Past research has applied neural networks [21], vector machines [15, 16], polynomial regression [22], and more on historical soil moisture datasets in the hydrology domain. However, none of them built a system from the Precision Agricultural perspective that took a holistic approach by addressing problems in both collection and analysis.

VII. FUTURE WORK

Future work on our soil moisture collection and prediction system should focus on testing on a large scale. Most of the work in this paper focuses on prototyping a reactive sensor node; the performance of the wireless sensor network when deployed at large scale in real world is not tested. Battery life, unit cost and long-term reliability play important roles in sensor deployment and should be addressed in future. On the prediction side, in our prediction experiment, we assume the forecasting data are error-free. Applying real, noise-included weather forecasting data onto models can be done in future work. Lastly, more advanced techniques in machine learning can be explored to reduce the amount of data required to achieve a good model. Currently, obtaining a fairly good model requires at least one year of data. Methods that include spatial factors into the modeling and achieve a fairly good model with less data are potential areas for future research. Using machine learning to study the temporal-spatial variations within one site is worth exploring as well, as it may result in more fine-grained models.

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