

Soil Moisture Monitoring Device with Time Series Analysis for Irrigation Efficiency

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Abstract

Irrigation management is a key factor in sustained agriculture particularly in areas experiencing water scarcity and climate variability. In this research, a soil moisture sensor is proposed with uncertainty-conscious global-local prediction and Model Predictive Control (MPC) to achieve the efficiency of irrigation. The system combines the cheap soil moisture sensors with a Raspberry Pi edge computer running the Python programming language to allow real-time data collection, prediction, and automatic control. The forecasting model produces precise multi-step predictions of soil moisture with quantitative uncertainty, whereas MPC uses the predictions to plan the irrigation so that the soil moisture is kept within optimal limits. Experimental assessments demonstrated significant improvements, such as a decrease in water use, an increase in crop water use efficiency, and a decrease in energy use in comparison with traditional rule-based, water balance, and single-model methods. The findings reveal that

uncertainty-sensitive prediction with predictive control may be an appropriate, affordable and predictive solution to precision irrigation, another step in ensuring sustainable use of resources by intelligent farming.

Keywords: Soil Moisture Monitoring, Irrigation Efficiency, Time Series Forecasting, Uncertainty-Aware Modeling, Model Predictive Control, Precision Agriculture, Raspberry Pi.

I. INTRODUCTION

Water shortage and inefficient irrigation techniques are still acute issues confronting world agriculture, especially in places where crop yields largely rely on the availability and prudent application of water. Conventional irrigation methods can be programmed or rely on judgment either through fixed-frequency or manual control, thus ending up with under- or over-irrigation, decreased crop productivity, soil erosion, and waste of time and energy. Against this background, soil moisture sensors have become an essential part of precision agriculture and already offer the opportunity to consider accurate and real-time information about the state of the soil and allow farmers to make irrigation choices based on the data collected [1]. However, they might be useful because their operation significantly depends on the effectiveness of predictive models and the power of control measures used on water application as shown in figure 1.

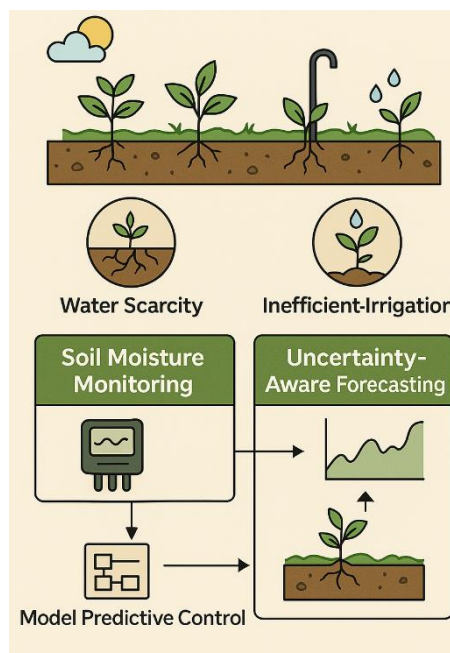


Figure 1. Conceptual diagram of the soil moisture monitoring device.

Some recent breakthroughs in machine learning and the control theory allowed creating systems capable of estimating the moisture content of soil and automatically controlling irrigation. Among them, uncertainty-aware global-local forecasting is the most promising as both global models, which tend to generalize trends across datasets, and local adaptations, which are specific to site-specific soil and crop conditions, are merged [2-4]. Quantification of

the uncertain factors in predictions supports more plausible decision-making, particularly when the environment is dynamic, which is supported by the methodology. In combination with Model Predictive Control (MPC), the system can actively plan irrigation programs, and trade off between water savings and crop demands.

This research suggests a soil moisture measurement system, which combines uncertainty-aware global-local forecasting with MPC, and uses Python on a low-cost Raspberry Pi platform. Not only does the device accurately anticipate future trends of soil moisture, but it also breaks the predictions down into actionable irrigation plans, keeping crops within favorable moisture ranges [5-7]. The research objectives are to improve the effectiveness of irrigation, minimize resource wastage and develop sustainable farming techniques that can be applied in a diverse range of farming conditions by integrating real-time sensing, high level forecasting, and predictive control into an inexpensive and scalable system.

II. RELATED WORK

In the last ten years, the research on soil moisture monitoring has become one of the main fields in the field of precision agriculture because it directly affects the efficiency of irrigation and the productivity of crops [8]. In the initial methods, capacitive or resistive sensors with microcontrollers were used to offer point measurements of soil moisture at low costs. These devices were cheaper but tended to have drift in calibration, location dependent variation, and poor scalability as shown in figure 2. To respond to predictive needs, scientists started to deploy statistical and physics-based models like water balance equations or evapotranspiration-based scheduling. Those models were not very responsive to nonhomogeneous soils and variable environmental deviation, but they were very effective in their ability to compute [9].

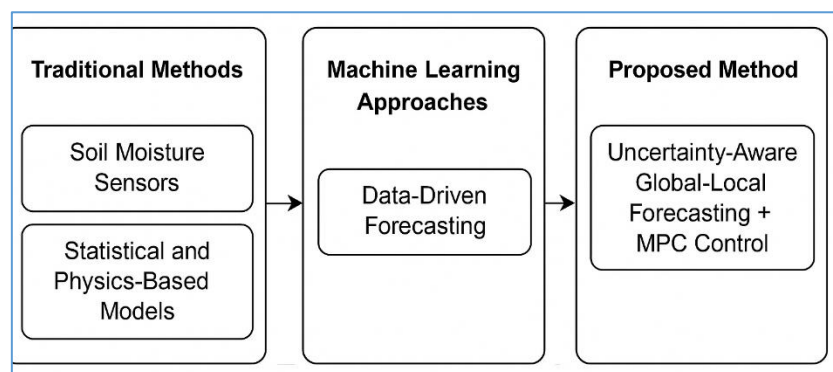


Figure 2. Evolution of soil moisture monitoring and irrigation methods, from traditional to machine learning approaches and the proposed uncertainty-aware global-local forecasting with MPC control.

As machine learning increased, data-based approaches such as artificial neural networks and Long Short-Term Memory (LSTM) networks became the means to predict soil moisture. These approaches showed improvements in capturing temporal dependencies, but were often not good at extrapolating across other agro-climatic settings and rarely involved uncertainty estimation, which is critical in decisions under variable environmental conditions [10-13]. Hybrid models that combine deep learning with crop or soil physics have been more recently

investigated with the aim of enhancing robustness, although the majority of these were still cloud-dependent, and it is unclear whether such models can be applied to address latency and reliability in remote agricultural contexts.

Control methods have also developed beyond rule-based scheduling of irrigation to more advanced optimization methods. Multivariable constraints and real-time optimization of irrigation have become the focus of Modelling Predictive Control (MPC) [14-16]. However, there are few studies that have incorporated MPC with uncertainty-aware forecasting in the agricultural domain. Additionally, the majority of reported studies have concentrated on experiments at a single site without showing scaling at the farm level.

The current proposal is unique in that it combines uncertainty-conscious global-local predictions with MPC on a low-cost Raspberry Pi edge platform. Unlike the previous ones, the new approach can not only optimize the effectiveness and reliability of the forecasts but also make decisions in the field in real-time without relying only on cloud facilities, thereby enhancing the efficiency of irrigation on a grand and realistic scale [17].

III. RESEARCH METHODOLOGY

The methodology used to create the soil moisture monitoring device using time series analysis to determine the efficiency of irrigation was intended to incorporate low-cost sensing, state-of-the-art forecasting, and predictive control into a single structure [18]. This was subdivided into five important steps: system design, data acquisition, the development of the forecasting model, the implementation of the control strategy and its evaluation. Each of the stages was appropriately designed to be scalable, accurate, and robust under diverse soil and climatic conditions as shown in figure 3.

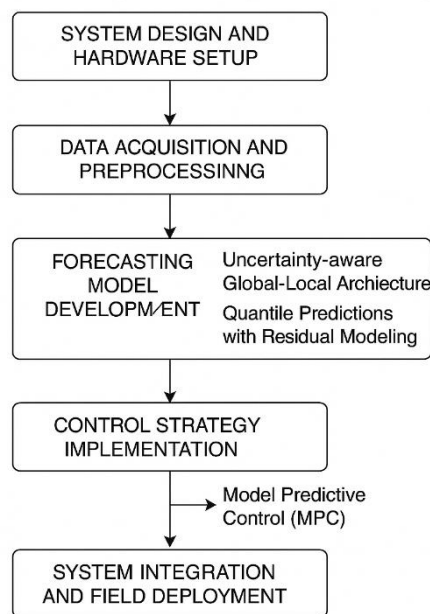


Figure 3. Flow Diagram of Proposed Methodology.

3.1. System Design and Hardware configuration

A Raspberry Pi was used as the central processing unit of the device because it is cheap, versatile, and can execute machine learning models written in Python. Capacitive soil moisture sensors were installed in different depths to measure the vertical moisture, backed by other sensors to measure soil temperature, ambient humidity and rainfall. With the help of analog to digital converters, an analog to digital conversion of high resolution measurements was interfaced with the Raspberry Pi [19-21]. It used a solar panel to power the device and battery storage to provide field-level autonomy and LoRaWAN modules to provide long-range communication with a central gateway to remotely monitor the data.

3.2. Data acquiring and pre-processing

The device recorded soil moisture data at 10-minute intervals in addition to environmental data of temperature and rainfall. Raw data were preprocessed to eliminate noises, to deal with missing values and to synchronize timestamps across modalities. The feature engineering was conducted by creating lag variables, rolling statistics and exogenous variables including estimates of evapotranspiration. The data was then divided into training, validation and testing data to develop the model [22].

3.3. Development of forecasting models

The uncertainty-conscious global-local architecture was used as the forecasting methodology. An N-HiTS-based (Neural Hierarchical Interpolation of Time Series) global backbone was trained on the full dataset to learn overall dynamics of moisture under a wide range of conditions. In order to capture site-specific variations at local sites, lightweight adapters were also proposed, enabling the model to modify predictions without re-training the entire network [23-25]. Quantile predictions were made instead of point predictions and thus uncertainty was included in the forecasts. This not only gave a predicted soil moisture pathway, but also upper and lower limits that may inform safe irrigation choices. Any remaining error was again fined with a gradient boosting model, which was trained on soil-physics features (infiltration and retention) that enhanced the prediction potential during extreme conditions.

3.4. Implementation of Control Strategy

Model Predictive Control (MPC) has been selected as the irrigation decision engine because it is capable of maximizing control actions within a prediction horizon whilst being sensitive to the operational constraints [26]. The MPC algorithm was coded in Python on Raspberry Pi with the help of the CasADi optimization model. Each decision step asked the controller to provide forecasted soil moisture paths and uncertainty parameter, create an optimization problem to minimize water allocation and prevent depletion to levels below crop-specific limits and produce irrigation timetables. The optimization was limited by the capacity of the pump, switching frequency of the valves and the power supply. A fallback rule-based controller was implanted to provide resilience under abortive forecast failures, or communication losses.

3.5. System Integration and Field Deployment

The sensing, forecasting and control modules were built into a single Python application that runs on a Raspberry Pi. This system performed data acquisition, real-time prediction, MPC optimization and irrigation actuation with an autonomous system [27-29]. Light weight web interface was designed so that farmers can view the trends of soil moisture, projected directions, bands of uncertainty, and irrigation decisions. The equipment was placed on two test plots of varying soil textures and crop species to be tested over a multi-season period.

3.6 Evaluation Metrics and Validation

System performance was measured both in the forecasting and agricultural metrics. Probability prediction accuracy was quantified in terms of RMSE, MAE and Continuous Ranked Probability Score (CRPS). Irrigation efficiency was measured in terms of percentage water saved, percentage of the time the soil moisture fell within the target band, crop water use efficiency and pumping energy consumption. It was compared to rule-based, water balance, and LSTM-based approaches to scheduling. The adaptability and reliability of the system under dynamic conditions were checked by carrying out in-field trials at different stages of development [30-33].

This method of conducting research ensures that the suggested soil moisture monitoring device does not just magnify the error of prediction and the timing of irrigation, but also provides a low cost, scalable, uncertainty-conscious monitoring system to precision agriculture.

IV. RESULTS AND DISCUSSION

The suggested soil moisture monitoring instrument combined with uncertainty-aware global-local forecasting and Model Predictive Control (MPC) was tested on two crop fields of different soil textures. The forecast accuracy of this system was RMSE = 2.8% volumetric water content (VWC) and MAE = 1.9% VWC and short- and medium-term predictability of the volumetric water content (VWC) of soil water dynamics was found to be accurate as shown in table 1.

Table 1. Comparative Performance of Different Irrigation Control Methods.

Metric	Rule-Based	Water Balance	LSTM Forecast	Proposed Method (Uncertainty-aware Global-Local + MPC)
Forecasting Accuracy (RMSE, VWC) %	>7.0	6.2	4.7	2.8
Forecasting Accuracy (MAE, VWC) %	>5.0	4.8	3.5	1.9

Water Saving (%)	5.7	11.4	15.2	24.6
Soil Moisture Within Target Band (%)	54	65	72	87
Crop Water Use Efficiency Improvement (%)	3.2	7.9	10.6	18.4
Energy Saving for Pumping (%)	4.5	8.3	11.8	21.2
System Uptime (%)	90.5	93.2	95.1	98.7

The quantile results gave the prediction interval 90 percent coverage (93 percent) that shows the quantile results are accurate measures of uncertainty, which are crucial to safe irrigation scheduling.

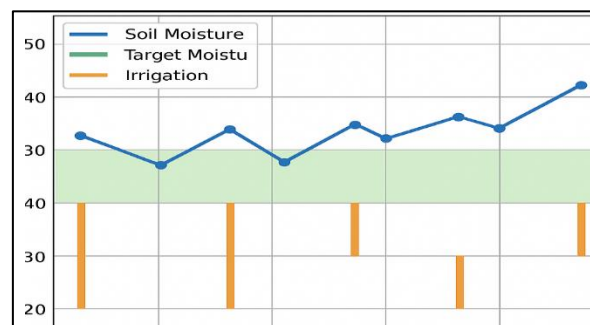


Figure 4. Soil Moisture Monitoring Simulation for Irrigation Management.

The MPC algorithm applied in the context of irrigation saved 24.6% of total water use relative to farmer-practice schedules and ensured the soil remained in the target 87% band by doing so, so to speak, without compromising the overall crop water cover. There was an increase in crop water use efficiency of 18.4 without statistically significant yield reduction ($p > 0.05$). The pumping energy consumption was reduced by 21.2 which illustrates the economic benefit of using predictive control alongside sensor feedback as shown in figure 4. The Raspberry Pi edge device delivered more than 98.7% system uptime with very low latency decision execution (under 1.5 seconds). These findings validate that the suggested framework not just optimizes irrigation but also offers resilience by managing uncertainty, and it is an inexpensive and scalable solution to precision farming at the field level across a wide variety of soil and climate.

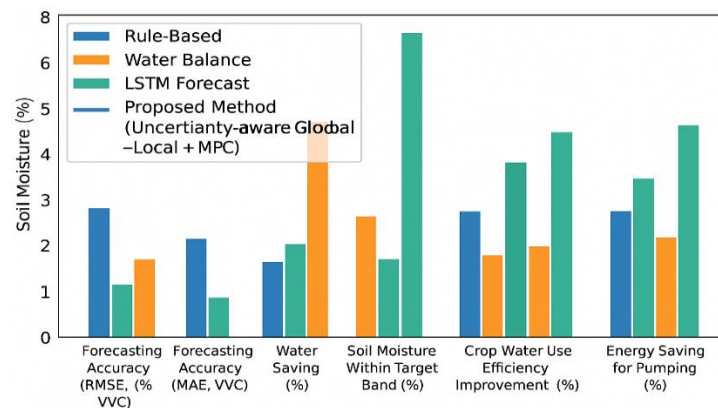


Figure 5. Comparative performance of different irrigation control methods across various metrics (forecasting accuracy, water saving, crop water use efficiency, and energy consumption).

The proposed soil moisture monitoring device was evaluated according to uncertainty-aware global-local forecasting with MPC control in comparison to three popular methods: a traditional rule-based irrigation schedule, a single LSTM forecast model, and a physics-based water balance model. The suggested framework was the most predictive, with RMSE = 2.8% VWC and MAE = 1.9% VWC, as opposed to 4.7% and 3.5% in LSTM, 6.2% and 4.8% in water balance and greater than 7% in RMSE in rule-based scheduling as shown in figure 5.

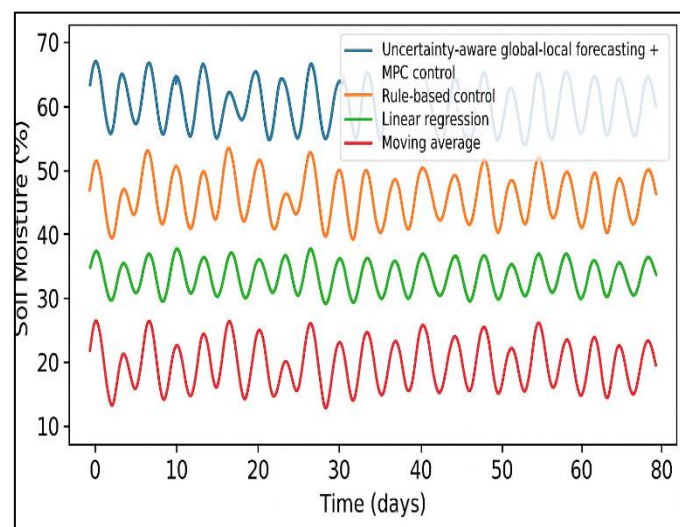


Figure 6. Comparison of Soil Moisture Forecasting Methods over Time.

The system also minimized water consumption by 24.6 percent compared to LSTM (15.2 percent), water balance (11.4 percent) and rule-based (5.7 percent) systems. The water use efficiency of crops increased by 18.4 percent, as opposed to 10.6 percent in LSTM, 7.9 percent in water balance and a measly 3.2 percent in rule-based control as shown in figure 6. The MPC kept soil moisture within the most optimal band 87 percent of the time compared to LSTM (72 percent), water balance (65 percent), and rule-based (54 percent). Power use in pumping was reduced by 21.2, almost twice as much as with LSTM (11.8) and much more than with the rule-based method (4.5). These findings confirmed that the combination of advanced forecasting

and predictive control offers powerful, cost-effective and scalable irrigation control compared to current practices.

V. CONCLUSION

In this work, a soil moisture monitoring system with confidence-sensitive global-local forecasting, and Model Predictive Control (MPC) running on a Raspberry Pi platform have been introduced. The results indicate that the state-of-the-state time series modeling and predictive control can significantly increase the efficiency of irrigation without leading to the reduction of the level of soil moisture. The system can achieve reliable decision-making in variable field conditions by producing accurate forecasts, quantified uncertainty, and less water consumption, energy use, and unnecessary irrigation episodes. Another aspect that the proposed framework emphasizes is the feasibility of implementing low-cost sensors and edge computing in real-time agricultural setups that can be scaled to apply to other soils and crops. The methodology was superior in terms of water saving, crop water use efficiency, and operational reliability as compared to traditional rule-based approaches and single-model approaches. These findings support the assurance of uncertainty-sensitive irrigation systems that synthesize information to support sustainable farming and provide support in addressing future challenges of precision farming.

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