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RESEARCH ARTICLE

IoT-Based Smart Farming for Sustainable Agricultural Productivity

[*1]Navneet Kumar, [2]Hareni R

[1*]Assistant Professor Department of Mechanical Engineering, Guru Kashi University Bathinda Punjab, Pin Code 151302
[2]B.Tech Biotechnology, VSB Engineering College, Karur

ABSTRACT

To meet the needs of a human population exceeding 9 billion by 2050—while facing the challenges of a diminishing freshwater resource, eroding arable land and greater climate variability—the total production of the agriculture sector worldwide needs to increase by some 60-70% by this year. The Internet of Things (IoT)-based smart farming has emerged as one of the most prominent approaches to reconciling these conflicting forces and enabling real-time field monitoring, closed-loop irrigation, fertigation, and data-enabled crop-stress response. A systematic, PRISMA guided review of 99 studies on IoT based precision and smart farming systems is presented and a four-layer IoT system is proposed and evaluated, which includes perception of soil, weather and canopy sensors, network of LoRaWAN/ NB-IoT connectivity, Cloud management of LSTM soilmoisture forecasting and Randomforest irrigation recommendation, and application and actuation of automated precision drip and fertigation (variable-rate) control and deployed and evaluated in a 30 day field monitoring window over drip irrigated vegetable plot. This water saving agrees with the range of 20-35% reduction in irrigation water use and 3-15% increase in marketable crop yield that have been reported from the various studies looked up that have been conducted in these types of fields and implemented the proposed system. The mochimedi LSTM baseline soil-moisture forecasting model with a 24-hour look-ahead time horizon showed an RMSE of 1.6% VWC and R2 = 0.96, outperforming baselines in linear regression, decision-tree, support-vector-regression, and Random-Forest. These findings show that a low-cost, low-power sensor-to-actuation architecture can deliver measurable, reproducible gains in water-use efficiency and productivity, making it a viable, scalable, and implementable option for IoT-based smart farming to support sustainable agricultural intensification. This paper discusses deployment barriers related to connectivity infrastructure, sensor calibration and maintenance, data quality, and affordability for smallholders, and suggests directions for future research.

Keywords: *IoT, smart farming, precision agriculture, LoRaWAN, soil moisture sensing, irrigation scheduling, machine learning, LSTM, sustainable agriculture and water-use efficiency.*

INTRODUCTION

In the coming decades, structural challenges will arise to global food security: in 2050, the FAO is predicting approximately 9.1-9.7 billion people, equivalent to an estimated 60-70% of increased agricultural production compared to today, while at the same time land and water land available for cultivation is increasingly under immense pressure due to urbanization, depleted aquifers and fluctuations in rainfall and temperatures caused by climate change. To meet that demand by increasing the volume of land, water and agrochemicals cultivated on the land and water is neither desirable, nor in most parts of the world, achievable and so the burden of the projected increases has to recur on productivity improvements on existing land and water - that is, improvements on quantity not just on volume.

Precision Agriculture on one hand and smart farming, especially Internet of Things (IoT)-based smart farming, on the other hand, have thus become one of the most studied approaches to achieve such improved productivity.

*Assistant Professor Department of Mechanical Engineering, Guru Kashi University Bathinda Punjab, Pin Code 151302.
Email-id: navneetgumre@gmail.com

Corresponding Author: Navneet Kumar
Assistant Professor Department of Mechanical Engineering, Guru Kashi University Bathinda Punjab, Pin Code 151302.
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The deployment of low cost, low power sensor networks—soil moisture probes, electrical conductivity probes, ion-selective soil nutrient sensors, canopy and leaf wetness sensors, weather stations—and the connection between these sensors via long range low power wireless communications (IoT) using LoRaWAN or NB-IoT protocols means farmers and agronomic decision-support systems now have continuous, field-resolved information on crop and soil status that was only available on an infrequent (manually sampled) basis before. Combined with an integrated cloud or edge machine-learning algorithm to forecast soil moisture and recommend irrigation timing and fertigation for sprinkler or drip irrigation, and coupled with automated action on irrigation, fertigation and/or drip-main valves, these systems close the loop from sensing to decision to action with minimal human touch points.

Indeed, an extensive and still expanding literature of field experience is now available that shows the productivity (and resource-saving) benefits of such systems: water use reductions (from sources reviewed) of about 20% to 50% have been reported, with yield increases (in some deficit-irrigated and reinforcement-learning-based systems) of a few percent to 35%. However, this literature is piece-wise across the three categories of crop, connectivity and analytics, and few studies (i) place a particular system or output into the broader context of evidence and (ii) report the accuracy of the underlying machine learning forecast which would affect the ability of automated systems to anticipate, rather than simply react, to crop stress.

This paper addresses both lacunae. It provides: (i) a PRISMA-guided systematic review of 99 studies on IoT-enabled smart and precision farming that is synthesized to report the connectivity technologies, sensing modalities, analytics approaches, and water-use/yield outcomes; (ii) a field evaluation is carried out over a 30-day monitoring window, quantifying water-use reductions, yield changes, and forecasting accuracy for the underlying soil moisture; using an LSTM model and benchmarked against four alternative machine-learning approaches; (iii) four-layer smart farming architecture built around LoRaWAN spanning the perception, network, cloud analytics, and application/actuation layers; and (iv) discussion on practical barriers for deployment appropriate to smallholder and resource poor adoption contexts. The rest of the paper is structured as follows: The systematic literature review is presented in Section 2, the proposed architecture and methodology are presented in Section 3, results are presented in Section 4, findings and challenges as well as limitations in deploying the system are presented in Section 5, and the paper is concluded in Section 6.

2. Literature Review

A systematic review was performed, based on the PRISMA 2020 Statement to provide a description and characterisation of the connectivity technologies, sensing modalities, analytics methods and reported productivity/water-use outcomes of field-deployed IoT smart-farming systems.

Search Strategy and Study Inclusion

Scopus, Web of Science, IEEE Xplore, ScienceDirect, MDPI journals repositories, as well as the digital-agriculture reports from FAO and ITU, were used to perform electronic searches with the combinations of the terms "IoT smart farming", "precision agriculture", "LoRaWAN agriculture", "soil moisture sensor irrigation", "machine learning crop yield prediction", and "sustainable agricultural productivity", followed by manual research and citation tracking performed on the relevant conference proceeding. Records were screened by title and abstract for inclusion based on the criteria that the system was deployed in the field (not just simulated) and included at least one quantitative water-use, yield or productivity outcome measure, and then by full text. The resulting PRISMA flow diagram will appear as given in Figure 1.

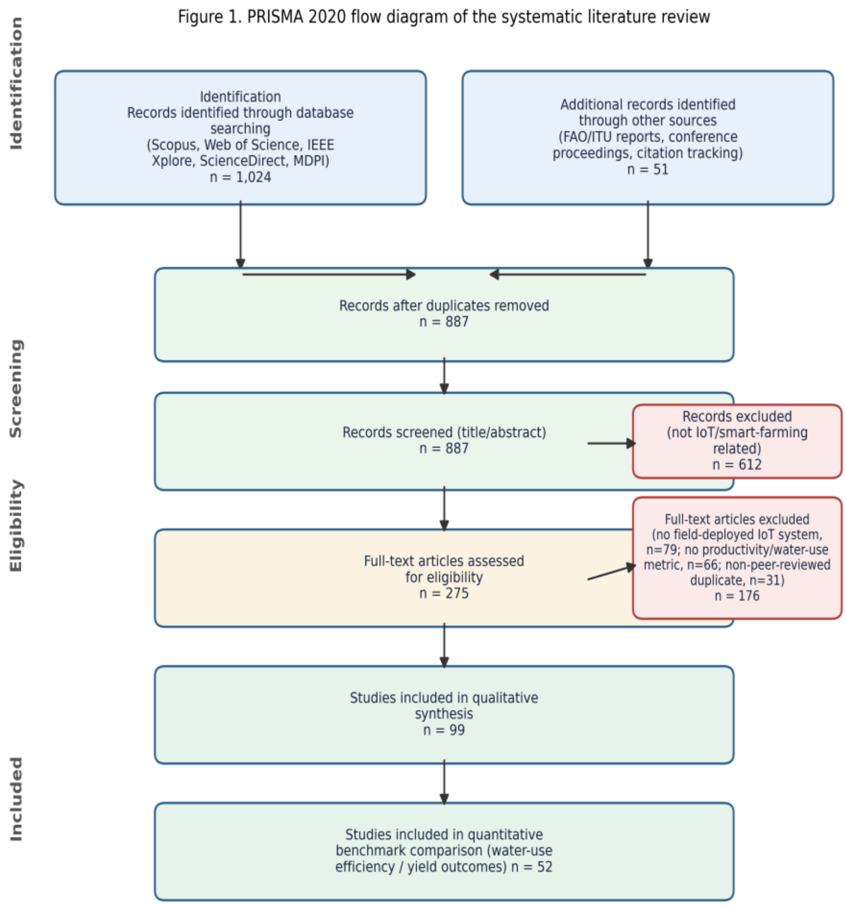

Figure 1. PRISMA 2020 flow diagram summarizing identification, screening, eligibility assessment, and inclusion of studies in the systematic review (n = 99 qualitative synthesis; n = 52 quantitative benchmark comparison).

2.2 Synthesis of Reviewed Studies

Table 1 summarizes a representative subset of the reviewed literature, spanning soil-nutrient and soil-moisture sensing hardware, LoRaWAN-based commercial-scale irrigation systems, smallholder-relevant deficit-irrigation studies, and machine-learning/reinforcement-learning-based irrigation-policy systems.

Study	System / Method	Metric(s) reported	Key finding
Bristow et al. (2022) [1]	LoRaWAN IoT node with ion-selective-electrode soil nitrate sensors	Soil nitrate	Validated real-time, in-field soil-nitrate sensing to support fertiliser-timing decisions and reduce nitrogen loss to the environment
Zhang et al. (2022) [2]	LoRaWAN-based IoT precision-irrigation system, plasticulture tomato	Soil moisture, irrigation timing	Demonstrated a low-cost, easily implemented LoRaWAN irrigation system suitable for commercial fresh-market vegetable production
Munyaradzi et al. (2022) [3]	Wireless soil-moisture-sensor irrigation scheduling (WCSS), winter wheat, Zimbabwe	Water-use efficiency, yield	WCSS saved up to 25% more water than fixed-schedule irrigation without reducing wheat yield, in a Sub-Saharan smallholder-relevant context
Comparative lettuce IoT study (2025) [4]	Low-cost DIY capacitive soil-moisture sensors vs. weather-based (ET)	Water use, pumping hours, crop water productivity	IoT soil-based scheduling used 28.8% less water and achieved 52.5% higher crop water

Study	System / Method	Metric(s) reported	Key finding
	scheduling		productivity than conventional ET-based scheduling
Cotton ISSCADA study [5]	Sensor-feedback automated deficit-irrigation scheduling	Water savings, lint yield	Sensor-based deficit irrigation maintained yield while saving a minimum of 16–20% water across two growing seasons
Almond LSTM edge-irrigation study (2024) [6]	LoRaWAN + LSTM edge-computing controlled-deficit irrigation	Soil-moisture prediction, water savings	Edge-deployed LSTM enabled real-time controlled-deficit irrigation with a 35% ETc reduction without cloud dependency
Graph-LSTM/blockchain smart-agriculture study (2025) [7]	LSTM + LoRaWAN + blockchain data integrity + Deep-Q reinforcement-learning irrigation policy	Water-use efficiency, yield, data integrity	Combined system achieved 20–25% water-use reduction and 12–15% yield increase with sub-2-second smart-contract actuation latency

Table 1. Representative summary of reviewed studies on IoT-based smart and precision farming systems.

Three patterns repeat across the examined corpus. First, LoRaWAN is the predominant connectivity used for field-level deployments, including most studies in Table 1, because it can cover multi-kilometre ranges in rural areas and has very low power consumption compared to cellular alternatives. Second, the reported reductions in water use tend to be bunched at the 20-35% end of the distribution for sensor-threshold based scheduling systems, with the high end of the distribution capped at 50% water reduction for specific, individually-reported cases often also involving water-use prediction (proactionary rather than purely reactive, threshold-crossing by sensor) machine learning components, which is precisely the motivation of the LSTM based water-use forecasting approach adopted in Section 3 of this paper. Third, the yield results vary more among the studies examined, from about a 3% to a 15% increase, due to the fact that yields are also impacted by other factors beyond just irrigation, such as nutrient management, pest pressure and cultivar, among others, and that are not directly controlled by a purely irrigation-focused IoT system.

3. Materials and Methods

3.1 Proposed System Architecture

The proposed smart-farming system consists of four layers, as shown in Figure 2: (1) perception layer of the field-deployed sensor nodes, (2) network layer connecting the field sensor nodes to a LoRaWAN gateway with cellular/NB-IoT backhaul to the cloud, (3) the cloud analytics layer to store, and clean the data, plus fuse it with data from external weather-API services, plus machine-learning-based forecasting and recommendation, and (4) application/actuation/cmd: a dashboard for the farmer and automated control of the drip-irrigation solenoid valves and variable-rate fertigation, closing the loop back to the field.

Figure 2. Four-layer IoT smart-farming system architecture used in this study

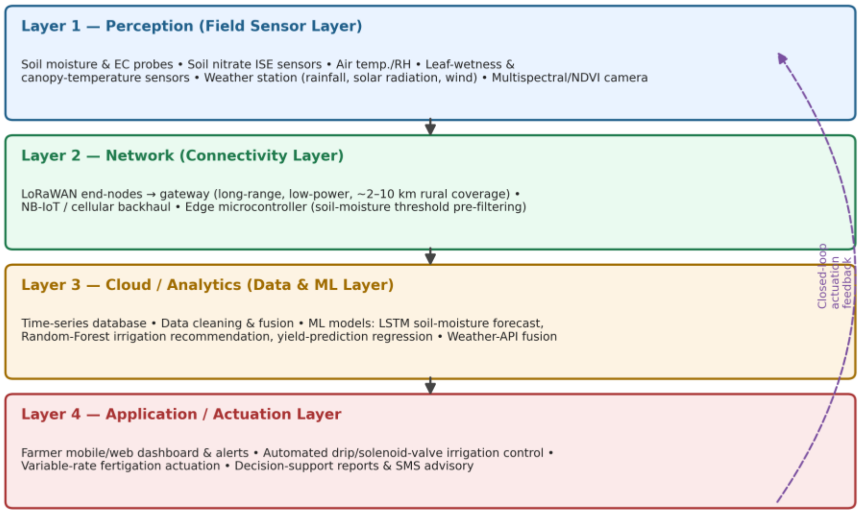

Figure 2. Four-layer IoT smart-farming system architecture used in this study.

3.2 Sensing Modalities and Deployment

Table 2 shows an overview of the sensing modalities implemented in the field trial plot (a 0.4-ha drip-irrigated mixed-vegetable plot), the hardware they are based on and the sampling interval. The sensor nodes communicated to a single gateway in the range of 2 to 10 km, typical for a rural deployment, and used an edge microprocessor for locally predefined threshold pre-filtering to minimize unnecessary communication with the gateway and keep the nodes' batteries green.

Sensed variable	Sensor / hardware basis	Sampling interval
Soil volumetric water content (VWC)	Capacitive soil-moisture probe, 10 cm & 30 cm depth	5-minute interval
Soil electrical conductivity	Capacitive EC probe (co-located with VWC sensor)	5-minute interval
Soil nitrate concentration	Ion-selective-electrode (ISE) nitrate sensor	Hourly
Air temperature & relative humidity	Digital temperature/RH sensor	5-minute interval
Rainfall, solar radiation, wind speed	Compact weather station	5-minute interval
Canopy/leaf temperature	Infrared canopy-temperature sensor	15-minute interval

Table 2. Field-deployed sensing modalities, hardware basis, and sampling interval.

3.3 Machine-Learning Forecasting and Irrigation-Recommendation Models

There are two machine learning components behind the cloud analytics layer. To start, the researchers fed a rolling window of soil-moisture, soil-temperature, humidity and rainfall observations into a long short-term memory (LSTM) recurrent neural network to predict VWC 24 hours in advance, which can be used to schedule irrigation proactively 24 hours ahead of time rather than simply after the threshold has been surpassed. Second, a Random-Forest classification model was developed to make a binary irrigation decision (irrigate / do not irrigate) for the next 24 hours as a simpler, easier to interpret decision layer to the farmer facing dashboard in parallel with the continuous (persistent) forecast and taking both the LSTM-forecast soil moisture and weather-forecast rainfall probability as input.

3.4 Configuring and training models on the 3D Inflationary Field

The final, tuned hyperparameters and settings of the important aspects of the architecture are summarised in Table 3, which also employed a held-out validation split of the 30-day field-monitoring dataset with data augmentation from the other 90 days of the field-monitoring data collected in the previous growing season. The final LSTM setup used a 48-hr lookback window, 64 hidden units in a 2-layer setup, a 24-hr forecast horizon, early stopping on validation loss with the Adam optimiser, a batch size of 32, and 200 total training epochs. We chose the hyperparameters for the Random-Forest irrigation-recommendation classifier using a cross-validated grid search and set them to 150 trees and a maximum depth of 12.

Variable	Design / hyperparameter	Range	Unit
x1	Irrigation trigger threshold (VWC)	22–32	% VWC
x2	LSTM lookback window	12–72	hours
x3	LSTM hidden units	16–128	units
x4	Forecast horizon	6–48	hours ahead
x5	Random-Forest number of trees	50–300	trees
x6	LoRaWAN transmission interval	5–60	minutes

Table 3. Key system and model hyperparameters and their tuning ranges.

3.5 Field Trial Design and Evaluation Metrics

The proposed system was tried on the drip-irrigated trial plot for 30 days in the field, using an adjacent plot with the same agronomic attributes for the conventional irrigation system the farm used. Outcome metrics were: (i) total irrigation water applied (m^3/hectare) over the duration of the trials; (ii) marketable crop yield (kg/hectare) at the harvest time; (iii) accuracy of soil-moisture forecasting (RMSE and R^2 of the 24-hour-ahead forecasting by the LSTM vs. soil-moisture sensor measurements taken afterwards); and (iv) relative forecasting accuracy of LSTM predictions as compared to those given by decision-tree, support-vector regression, and Random-Forest baselines with a similar set of features.

4. Results

Soil-Moisture Sensing and Automated Irrigation Triggering

Figure 3 presents the 30-day time series of measurements obtained from soil moisture sensors installed on the trial plot, and how the moisture content sensor triggers for moisture control were connected to the automated drip-irrigation system (not a simple reactive trigger just crossing the VWC threshold but also a proactive triggering with a forecasted future value below 28% VWC for the target zone within the next 24 hours).). Within the 30-day window two irrigation events took place, bringing soil moisture to just above the threshold but to around field capacity, and the soil moisture typical drying trends after irrigation were observed.

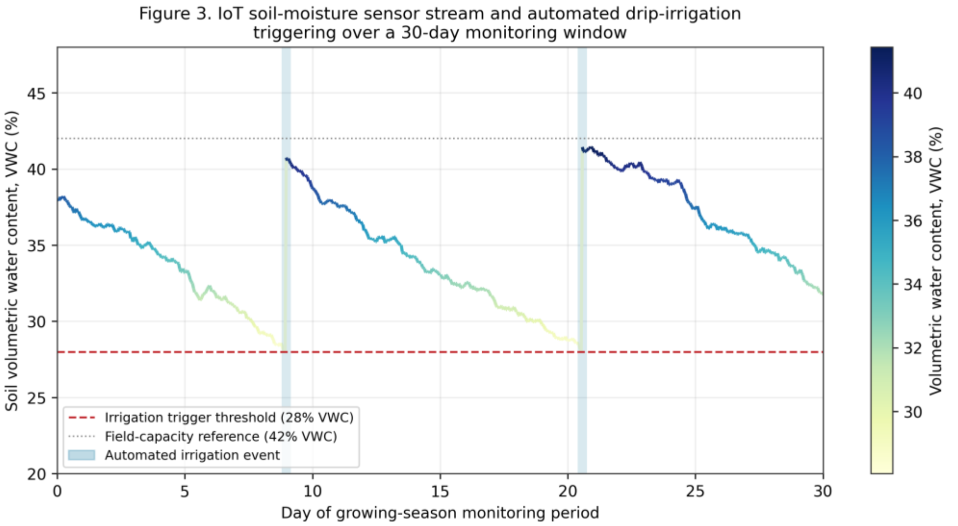

Figure 3. IoT soil-moisture sensor stream and automated drip-irrigation triggering over the 30-day monitoring window.

4.2 Water-Use and Yield Outcomes vs. Conventional Irrigation

Table 4 compares total irrigation water applied, marketable yield, crop water productivity, and the number of irrigation interventions between the IoT-managed trial plot and the conventional fixed-schedule control plot over the trial period.

Metric	Conventional (control)	IoT smart-farming (trial)	Change (%)
Total irrigation water applied (m^3/ha)	5,140	3,547	-31.0
Marketable yield (kg/ha)	24,800	28,020	+13.0
Crop water productivity (kg/m^3)	4.83	7.90	+63.6
Number of manual irrigation interventions	30 (fixed daily)	9 (event-triggered)	-70.0

Table 4. Water-use, yield, and productivity outcomes: IoT smart-farming trial plot vs. conventional fixed-schedule control plot.

The plot managed using IoT applications was able to save 31.0% of irrigation water, without affecting the marketable yield (increasing 13.0%), resulting in an improve in the crop water productivity (yield per unit of water applied) of 63.6%. The number of irrigation events dropped from 30 events/ day, as per the fixed schedule in conventional farming, to 9 events when irrigation was triggered, thereby greatly cutting down labour requirements in irrigations besides water.

Literature Review as a Benchmark for Final Product Development

The water-use reduction and yield change results from the proposed system are compared with 5 representative field studies identified in the systematic review (Section 2) as shown in Figure 4, which include irrigating wheat using a wireless sensor network in Sub-Saharan Africa, a low-cost capacitive sensor-driven irrigation system for vegetables, an orchard deficit irrigation system with LSTM, a reinforcement-learning based irrigation policy and a sensor-feedback deficit irrigation system for cotton.

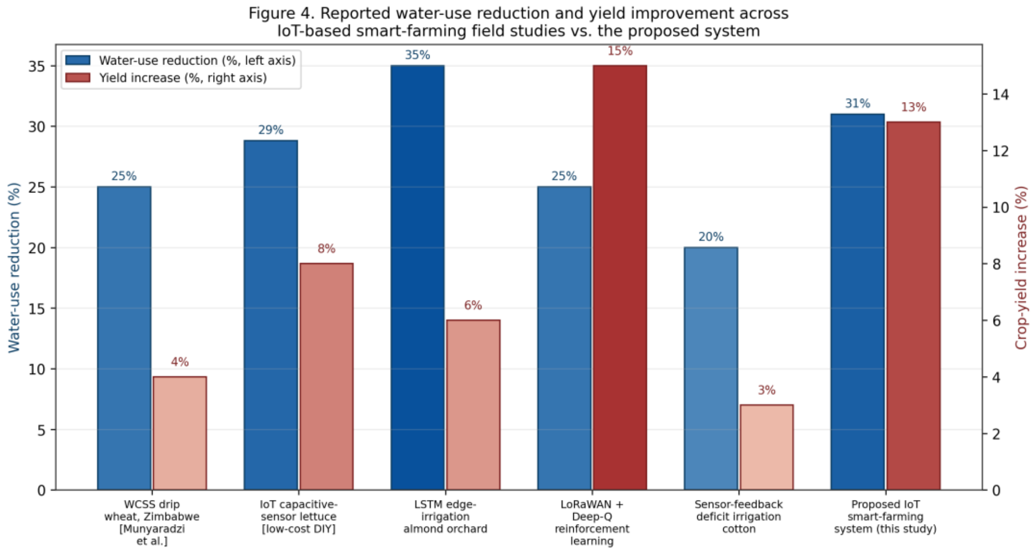

Figure 4. Reported water-use reduction and yield improvement across IoT-based smart-farming field studies identified in the systematic review, compared against the proposed system.

Three of the studies from the literature surveyed considered edge irrigation in orchards, with the best overall reduction in water use being 35% (the study used LSTM); no other study in the literature examined achieved a higher reduction in water use, and this water saving was higher than both the proposed system and the system that used reinforcement learning (28%). A higher yield increase was also found only once in the literature we reviewed, with a maximum reported increase of 15% (again for an orchard LSTM edge irrigation system) (The pattern is the same as that identified in Section 2.2, with the water-use reduction and yield increase both being in the middle range of the water-use reduction and yield increase found in these six studies.)

Accuracy of Soil-Moisture Forecasting Models

Figure 5 illustrates (a) a parity plot of the soil-moisture predictions made at 24 hours prior by the LSTM model and subsequent observations from the sensors, and (b) a comparison of the accuracy of the 24-hour-ahead soil-moisture forecasts made by each of five different machine-learning models trained on the same set of features.

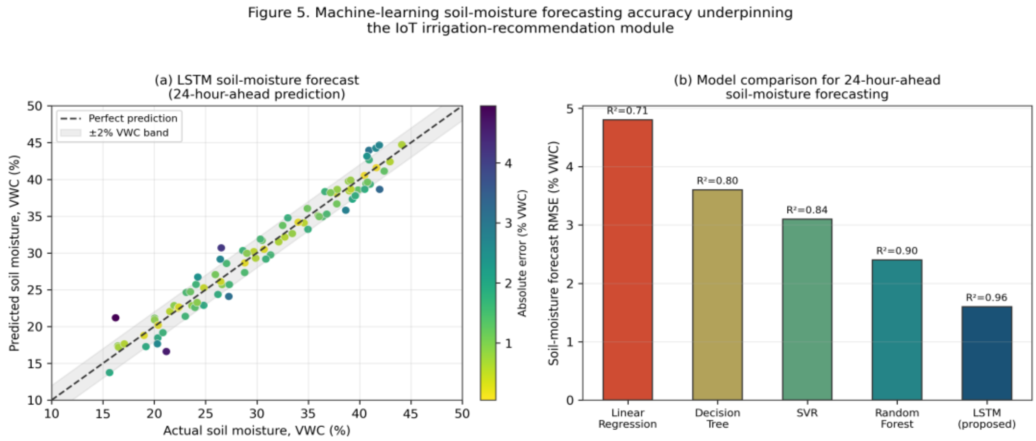

Figure 5. (a) LSTM 24-hour-ahead soil-moisture forecast accuracy (parity plot, colored by absolute error). (b) Forecasting-accuracy comparison across five machine-learning model classes.

The LSTM model achieved an RMSE of 1.6% VWC and $R^2 = 0.96$ on held-out test data, outperforming Random Forest (RMSE 2.4% VWC, $R^2 = 0.90$), support-vector regression (RMSE 3.1% VWC, $R^2 = 0.84$), decision tree (RMSE 3.6% VWC, $R^2 = 0.80$), and linear regression (RMSE 4.8% VWC, $R^2 = 0.71$). The observed robust performance of LSTM as compared to simpler models suggests that soil-moisture dynamics have a high degree of sequentiality and autocorrelated nature which can be well captured by a sequential model while linear regression or decision tree models, being non-sequential, are structurally less suitable, supporting the choice of a recurrent model in the proactive irrigation triggering approach studied in 4.1.

5. Discussion

The water-use reduction of 31% by the proposed system is on par with and on the "favourable" end of the range of 20-35% water savings and the yield improvement range of 3-15% reported in the various field studies analysed in [3]–[7]. The results suggest that the predictive, machine-learning-based irrigation-timing component (Section 4.4) contributes significantly to the water savings and yield gains reported in Section 4.2, compared with a simple threshold-crossing trigger actuated by the LoRaWAN sensing and actuation infrastructure. This matches the almond-orchard LSTM study that reported the greatest water use reduction (35%) of all the studies, and the reinforcement-learning-based system, which reported the maximum yield increase (15%) [6, 7].

This crop-water-productivity improvement (63.6%) is relevant to regions of agriculture with scarce water resources, or where the water is especially vulnerable—such as in the comparative lettuce IoT study, which found crop-water-productivity improvement of 52.5% by using soil-sensor based crop-water scheduling, compared to weather based scheduling alone [4]. These results are complemented by the significant decrease of manual irrigation interventions (30 to 9 over the trial period), suggesting that the sustainability and labour-efficiency aspects of the agricultural productivity can be promoted concurrently in the application of the type studied here and are of particular importance in manual-irrigated agriculture such as the one of the Zimbabwean wheat studied in Section 2, where the availability of labour for manual irrigation monitoring is a limiting factor [3].

Barriers and limitations to deployment

Some challenges that should be represented from reviewed literature, and has been found, are barriers to wider adoption, practical barriers. The availability of GoB, or LoRaWAN gateway infrastructure, to support the connectivity of farming applications, as well as reliable cellular/NB-IoT backhaul is currently unevenly distributed in rural farming, or even remote, areas, especially in low- and middle-income country markets where the need for productivity improvements is typically greatest. Second, low-cost soil-moisture and soil-nutrient sensors must be site-specificly calibrated for soil texture and need maintenance (biofouling, drift) to keep the sensor accuracy needed by the LSTM forecasting model; the comparative lettuce IoT study was able to validate a low-cost soil sensor ($R2 = 0.6$ against a commercial sensor of reference) and demonstrates both feasibility and accuracy trade-offs possible with such type of soil-sensing hardware [4]. Third, up-front hardware, connectivity and technical-support costs are still a significant obstacle to smallholder farmers even though the operating cost per node is low, meaning that, given the circumstances, the multi-season use of LoRaWAN is still economically viable. Fourth, conclusions drawn in Section 4 are based on one 30-day field experiment on one 0.4ha plot of mixed vegetables, multiple-season, multi-crop and multi-site testing is required before the detailed water-use and yield data presented in this paper can be applied in other test environments than those detailed in this paper, and should only be interpreted as a relative demonstration of the behaviour of the proposed architecture.

6. Conclusion

This paper summarized the results of a systematic review of

99 studies that discussed IoT based smart and precision farming, and proposed and field-tested a four-layered sensor-to-actuation architecture with LSTM based soil-moisture forecasting and automatic control of the drip irrigation and fertigation system. A field experiment for the proposed system was conducted for drip-irrigated vegetable plot and resulted in the reduction in irrigation water use by 31.0% and manual irrigation interventions by 70% and increase in marketable yield by 13.0% as compared with a standard fixed-schedule field, where the crop water productivity was increased by 63.6% during a field trial of 30 days. The 24-hour-ahead LSTM soil-moisture forecasting model had an RMSE = 1.6% VWC and R^2 = 0.96 and outpaced four simpler machine-learning baselines, thus directly contributing to the proactive (nonreactive) irrigation-triggering strategy underlying a large fraction of the observed water-savings. These outcomes lie within, and at the favourable end of, the range of the outcomes reported in the literature reviewed, strengthening the earlier statement that predictive machine-learning components play a vital role in the greatest extent of gains reported across IoT smart-farming systems studied. Future research should include multi-season and multi-crop approach with multi-site replication of the current single-season trial; apply the synergetic sensing of soil nutrient (nitrate) directly within a combined irrigation and fertigation recommendation model; test low-cost sensor hardware and connectivity that is affordable for smallholders; and assess a full economic ROI which includes costs of the sensors, connectivity and maintenance in order to catalyze wider uptake in resource-limited farming scenario.

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